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Chapter 1

General Introduction

Sales promotions within consumer packaged goods markets have been increasingly used as one of the main tools for both manufacturers and retailers to increase sales. A decrease in consumer willingness to pray premiums for national brands (Steenkamp et al. 2010) and an increase in willingness to visit multiple stores (Baltas et al. 2010) are amongst the main drivers of the increased use of sales promotions. Despite its popularity among retailers and manufacturers, the net effects of promotions are not always positive (e.g. Srinivasan et al. 2004). Not only are promotions a prevalent phenomenon in the industry, the academic literature has dedicated a large amount of attention to this topic. In specific, the literature has documented how promotions lead to promiscuous (switching) behaviour (e.g. Gupta 1988; van Heerde et al. 2004). Despite the fair share of attention that has been given to promotions in the literature, several key questions have remained as of yet unanswered. Jointly, the three chapters in this dissertation aim enrich the literature on sales promotions, by combining practical issues with the already rich existing literature.

The second chapter of this dissertation addresses the promotion calendar. Although there has been some attention to the scheduling of promotions, studies on the optimal timing of brand promotions have mostly been conducted at the market level, or within a retail chain (Mehta and Ma 2012; Silva-Risso et al. 1999; Tellis and Zufryden 1995; Zhang and Krishnamurthi 2004).

In Chapter 2, the co-occurrence of brand promotions across retailers is assessed. Specifically, this chapter focuses on store flyers featuring price cuts - around which planning of the promotional calendar typically revolves - to address the following set of questions. Does the calendar of featured price cuts for a national brand across retailers, affect the promotion outcomes for the manufacturer and the retailer? If so, what mechanisms bring about these differences, and what are the implications? Should a brand's featured price cuts be scheduled in-phase (simultaneously), or out-of-phase (asynchronously), across retail chains? Does the preferred calendar differ when it comes to gross sales lift, versus net sales gains or revenues? Are the interests of manufacturers and retailers necessarily unaligned? This chapter examines the mechanisms underlying out-of-phase vs. in-phase schedules, and empirically demonstrates their sales and revenue implications in four product categories, covering purchases of a national panel of households across eight years. The results reveal that calendar effects primarily materialize in categories where the chosen retailer is driven by brand promotions. In those categories, alternating the timing of featured price cuts across chains substantially increases the manufacturer and retailers' immediate sales lift. However, when it comes to net gains, striving for out-of-phase promotions – the dominant approach among chains – is not necessarily 'best practice': retailers see the revenue advantage diminish, and manufacturers may even earn less.

The third chapter of this dissertation focuses on the decomposition of the effects of sales promotions. Where previous literature has mainly analyzed the effect of promotions on an aggregate level (e.g. Srinivasan et al. 2004; van Heerde et al. 2004), or on store (e.g. Gauri et al. 2008) or brand choice (e.g. Mehta and Ma 2012), this study takes a disaggregate approach that looks at both brand and store choice. How individual households trade off their category purchases between brands and retailers, and how these (possibly heterogeneous) decision patterns align with the effects of feature and price discount promotions is as of yet not well documented. The interplay between manufacturers and retailers has become increasingly strained, making it critical to understand to understand the role of promotions in how shoppers choose among brands and stores, for the effective allocation and targeting of promotions sales budgets for both retailers and manufacturers. The primary objective of this chapter is to shed light on the patterns of brand-retailer choice in consumer packaged goods categories, and to explore how they affect the impact of promotions on the manufacturer and retailer. Using a flexible generalized extreme-value model, this chapter analyses the effect of feature and discount promotions in a multi-retailer and multi-brand setting, in which households can use different decision routes to choose a brand and store. Across nine different CPG categories, results reveal that in each category a mixture of decision routes prevails: about 55% of households exhibiting a brand focus (i.e. primarily select a brand, and then choose between stores offering that brand); the remaining 45% showing evidence of a retailer focus (i.e. rather substitute brand offers within a visited store). Not only do these decision routes entail different patterns of competition between brands and stores, they also come with differences in promotion response: feature ads triggering stronger (weaker) reactions among households with a brand (retailer) focus in almost all categories, and discount depth hardly affecting households with a retailer focus. As such, especially for less-frequently purchased categories, the brand-focus decision route leads to larger net promotion benefits for the retailer and, despite the stronger brand-cannibalization, even for the manufacturer. Managerial implications are discussed.

The fourth chapter of this dissertation deals with large-scale promotional events. A recent and as of yet largely unstudied phenomenon in grocery retailing is the use of “Savings

Weeks", i.e. large scale promotional events in which supermarket chains advertise promotions across multiple categories simultaneously, under a common theme, and across several weeks. A rigorous analysis of the countervailing forces is currently lacking, and this sets the stage for our current research. Specifically, we aim to address the following questions. First, how do large-scale "Savings Week" events at grocery chains affect store traffic and spending during promotion weeks? Do they attract extra visitors to the store? Do they increase current customers' spending at the store? And: to what extent do similar competitive events offset the impact of the retailer's own initiatives? Second, what are the dynamics involved? Do the Savings Weeks, given their 'recurrent' and 'recognizable' character, lead to negative lead effects? Do they come along with post-event dips in store traffic and spending? In an empirical analysis of 25 large-scale events by the four largest Hi-Lo Dutch retailers across a three-year period, we find that the fraction of consumers visiting the retailer during such a promotional event increases substantially (by up to 13%) and that, for the majority of events, average weekly spending at the focal retailer also goes up (by up to 10%) at the cost of visits and expenditure elsewhere. We find the store visit effects to be strongest for non-primary customers, while the absolute spending increase is largest for regular store visitors. Due to their recurrent character, the events give rise to modest lead effects (i.e. to a small degree consumers postpone their visits or spending prior to the event). In addition, consumers have a lower propensity to re-visit the store after the promotional event, yet spend slightly more than average in post-event weeks. Retailer implications are discussed.

Chapter 2

"Take Turns or March in Sync?" Impact of the National Brand Promotion Calendar on Manufacturer and Retailer Performance

2.1. Introduction

Sales promotions have become a dominant marketing instrument of consumer packaged goods (CPG) manufacturers and retailers. The share of products sold on promotion at HiLo chains has steadily increased over the past years – exceeding 20% for several retailers (GfK 2012). Especially price cuts supported by feature advertising have been found to entice consumers (Ailawadi, Beauchamp, Donthu, Gauri and Shankar 2009; Bijmolt, van Heerde and Pieters 2005). At the same time, there is growing concern about the net benefits that accumulate from these promotions. Even if featured price cuts lead to a large sales bump during the promotion week, they do not necessarily imply a net gain in sales volume or revenue (Ailawadi et al. 2009, Srinivasan, Pauwels, Hanssens and Dekimpe 2004).

A major threat for the manufacturer is that – instead of increasing category consumption or stealing sales from competing brands – the promotion bump comes at the expense of own brand purchases, in past or future periods (Neslin and van Heerde 2009) and/or in retail stores where it is not on promotion (van Heerde, Leeflang and Wittink 2004). Although evidence of direct store switching (i.e. consumers changing store allegiance because of promotions) is generally weak (see e.g: Srinivasan et al, 2004), promotions may trigger indirect store switching – consumers shifting category purchases among stores they already visit regardless of promotions (Bucklin and Lattin 1992). Indirect store switching may become more prevalent as a consequence of the increase in multiple store shopping (Gijsbrechts, Campo and Nisol 2008, Zhang, Gangwar and Seetharaman 2010). Promotions at one retailer are likely to attract regular brand customers from other retailers, who would have adopted the brand anyway at the regular price, and now simply shift stores (Srinivasan et al. 2004, Gauri, Sudhir and Talukdar 2008). Clearly, such shifts in purchase location are not beneficial for the manufacturer: they do not increase total brand sales, but only subsidize consumers (van Heerde et al. 2004). In contrast, store-switching is essential for the retailer, whose main promotion objective is to generate extra (category) sales by attracting consumers from rival chains (Ailawadi et al. 2009). As such, promotion-induced store shifts create a tension between the manufacturer and the retailer and place the timing of a brand's promotions across retailers high on the promotion-planning agenda.

According to anecdotal evidence and extant literature (Wierenga and Soethoudt 2009, Freimer and Horsky 2012) both the manufacturer and the retailer exert some influence on the promotion calendar. Typically, one party (either the manufacturer or the retailer, the dominant practice depending on the geographical setting and specific parties involved, Wierenga and Soethoudt 2009) proposes a calendar specifying the promotion weeks for the brand and retailer over the upcoming half-year. This proposed calendar is refined throughout the negotiation. The manufacturer can take into account the promotion times across all his retail accounts; the retailer, though not directly in control of promotions at competing chains[1], can steer the timing of these promotions by imposing restrictions on the manufacturer, i.e., urging him not to promote at rival chains in specific weeks.

The prevailing view is that retailers want '*exclusivity*'; they desire calendars in which the manufacturer brand is not promoted at competing chains in the same week (Wierenga and Soethoudt 2009, GfK Internal Report 2012). Manufacturers want *simultaneity*, because it takes away the incentive for consumers to 'cherry-pick' the brand between stores. Empirical evidence, however, does not point to exclusive use of one or the other practice. More importantly, the question remains: does it really matter and, if so, what type of schedule should each party strive for?

Practitioners have been increasingly preoccupied with this issue[2], but academic research has not followed suit. Studies on the optimal timing of brand promotions have mostly been conducted at the market level, or within a retail chain (Silva-Risso, Bucklin and Morrison 1999, Zhang and Krishnamurthi 2004, Tellis and Zufryden 1995, Mehta and Ma 2012). A likely reason is the complexity of the topic, which involves interrelated decisions by multiple parties (manufacturers and retailers), with various objectives that are often not aligned (brand and/or category sales, sales volume and/or revenue) and the outcome of which materializes through different consumer-response mechanisms over time. This makes an analytical approach virtually impossible (Freimer and Horsky 2008), and renders the decision highly challenging for

[1] Unless the calendar negotiations are performed by a buying group encompassing multiple retail chains – in which case the calendar proposal can include coordination of promotions across members of the buying group.
[2] Based on exchanges with, e.g., Inge Vening, (Consultant (ABS) at GfK), Suzan Jansen (Business analyst at GfK), Eijte Foekens, (Manager Commercial Analytics and Consumer Research at Jumbo Supermarkets & C1000, former Senior Manager Market Research at Albert Heijn), and retail account managers/members of the promotional planning group at Heineken.

the parties involved. Hence, there is no consensus on which calendar leads to better outcomes and why.

Our paper sheds light on this issue. Specifically, we focus on price cuts featured in the retailers' store flyer - around which the planning of this promotional calendar typically revolves - to address the following set of questions. Does the calendar of featured price cuts for a national brand across retailers, affect the promotion outcomes for the manufacturer and the retailer? If so, what mechanisms bring about these differences, and what are the implications? Should a brand's featured price cuts be scheduled in-phase (simultaneously), or out-of-phase (asynchronously), across retail chains? Does the preferred calendar differ when it comes to gross sales lift, versus net sales gains or revenues? Are the interests of manufacturers and retailers necessarily unaligned?

To address these questions we build on the research tradition initiated by Gupta (1988) and first identify the components that make up the consumers' promotion response. However, instead of focusing on one isolated promotion, we outline how the scheduling of featured price cuts across chains – in-phase versus out-of-phase – may affect the outcome for the manufacturer and the retailer. We then empirically test the effects in four product categories – beer, liquid laundry detergents, coffee and chips – covering households' store choice, category purchase incidence, brand choice and quantity decisions; in the presence of promotions by multiple brands, across grocery chains in the Netherlands. Our generalized extreme value model flexibly captures households' promotional response, and provides a tool to simulate and compare the impact of alternative promotion calendars.

Three points must be noted upfront. First, we consider the promotion schedules of a given (leading) brand manufacturer. Clearly, adjusting that manufacturer's calendar will automatically affect the timing of its promotions relative to those of competing brands. Though our analysis accommodates rival brand promotions, we largely treat them as exogenous. Consequently, our paper is limited in the sense that it does not accommodate strategic competitive reactions to changes in promotion calendars. We revisit this point in the discussion section. Second, similar to Srinivasan et al. (2004), we focus on sales and revenue within the category. Retailers, and multi-product manufacturers, may care about sales shifts induced by the promotion in other categories as well. Also, they may ultimately focus on profit (i.e. gross margin). Though our analysis is an important step towards assessing such profit implications, we will, for lack of data on pass through, only roughly explore those below. Third, real-life calendars are often a mixture of in-phase and out-of-phase promotions. By laying out the pros and cons of each and empirically assessing them in our simulations, we help managers trade off schedules with more 'in-phase' or more 'out-of-phase' promotions.

2.2. Impact of the Promotion Calendar

2.2.1. Background Literature

Starting from the seminal work by Gupta (1988), various papers have uncovered the response mechanisms that lead to promotional gains for the manufacturer (e.g. van Heerde et al. 2004) and the retailer (e.g. Ailawadi, Harlam, Cesar and Trounce 2006, Ailawadi et al. 2009). These efforts yield several insights relevant for our analysis: (i) although promotions lead to sizable immediate sales bumps, only part of this gross sales lift represents a net sales gain (e.g. Gupta 1988, van Heerde et al. 2004, van Heerde and Neslin 2008), (ii) the sources of this gain are different for manufacturers and retailers (e.g. van Heerde et al. 2004, Srinivasan, et al. 2004), (iii) promotion effects are asymmetric: some brands triggering stronger sales shifts away from their rivals than others (e.g. Blattberg and Wisniewski 1989; Sethuraman, Srinivasan and Kim

1999, Neslin 2002), and (iv) even if promotions result in a net gain in unit sales, their net revenue implications may be less appealing (Srinivasan et al. 2004, Ailawadi et al. 2009, Haans and Gijsbrechts 2011). Several consumer and market characteristics can enhance or reduce the magnitude of these effects, such as the size of the switching (deal-prone) versus loyal (non-responsive) segment (Narasimhan 1988, Freimer and Horsky 2012) and the possibility of market expansion (Freimer and Horsky 2012).

Our research builds on these insights. We analyze the sales and revenue effects of price cuts featured in the retailers' store flyer (hereafter 'promotions'). Instead of looking at the effect of each price cut in isolation, we study how the *scheduling* of a brand's featured price cuts throughout the promotion planning period, *across retailers* (i.e. its 'promotion calendar'), affects the outcome for manufacturers and retailers.

2.2.2. Sales Shifts under Alternative Promotion Schedules

Consider a manufacturer that, over the planning horizon, needs to schedule store-flyer appearances for its brand at a given set of retailers (hereafter, we refer to this brand as the *focal brand*; to the retailers involved in the promotion calendar – i.e. where the brand is promoted in at least some weeks – as the 'focal retailers'; and to retailers that never offer a featured price cut for the brand as 'non-focal' retailers). The timing of featured price cuts can follow (i) a more 'out-of-phase' schedule (with few overlapping promotion-weeks among focal retailers) or (ii) a more 'in-phase' schedule (in which the brand is, more often, featured simultaneously at different focal retailers). The key question is how does the promotion bump and its components, change as the brand moves from a more out-of-phase to a more in-phase calendar?

Even if the number of promotion events (weeks with a store flyer ad and price cut) for each retailer is decided/agreed upon, their *scheduling* across retailers may still affect the gains from the promotion calendar, for the manufacturer as well as the retailers. To show this, we first list the components that make up the consumers' promotion response. Next, we explain how different promotional calendars affect each component.[3]

Within the promotion period, sales of the focal brand at the promoting chain consist of baseline sales, plus the promotional sales bump or 'gross sales lift'. This lift partly results from shifts *within* the promotion week, made up of: brand switching (consumers shifting purchases within the promoting store, from a rival brand to the focal brand), store switching (consumers buying the focal brand at the promoting chain, rather than a rival chain), brand-store switching (consumers buying the focal brand at the promoting store, instead of a rival brand at another store) and category expansion (consumers buying and using more of the focal brand at the promoting chain). The promotion may also induce sales changes in preceding weeks (in case consumers anticipate it, and postpone their purchases) or subsequent weeks (due to consumers stocking up or repeat buying); this can be classified as pre-emptive brand switching (accelerated or delayed purchase shifts away from rival brands), pre-emptive store switching (forward buying or postponed purchases away from rival stores), pre-emptive brand-store switching (accelerated or delayed purchases away from non-focal brands and stores) and stockpiling (accelerated (postponed) baseline purchases from future (previous) periods, or, alternatively, post-promotion category expansion).

Comparing these promotion components between calendars, two main differences become apparent. First, more 'in-phase' calendars should result in smaller cross-store shifts. If promotions run concurrently, even though customers of non-focal chains (i.e. where the brand is

[3] As noted by Leeflang, Selva, van Dijk and Wittink (2008), brand promotions can trigger (minor) sales effects in other categories. Similarly, Ailawadi et al. (2006) point to possible 'halo effects': shoppers attracted to the store by a promotion also purchasing other categories. While we focus on within-category effects - the bulk of the promotion impact (Ailawadi et al. 2006, Leeflang et al. 2008) - we revisit broader store-switching implications subsequently.

never promoted, see above) may shift towards the promoting stores, focal-chain customers have little to gain from store switching, as they can buy the brand on promotion in their 'customary' store. In contrast, if the promotions alternate in time, customers *do* have an incentive to shift purchases between focal stores (i.e. *from* the non-promoting *towards* the promoting store *in that period*) to benefit from the deal on offer. Hence, we expect out-of-phase calendars to entail more (immediate) store- (and, possibly, brand-store) switching.

Second, the 'spread' of promotions in more out-of-phase calendars means a larger number of 'promotion' weeks (in which at least one chain has the brand on promotion). On the one hand, this may result in 'deal-to-deal' buying (as consumers postpone their purchase in anticipation of the next price cut); consumers may also not stock up in large quantities, thereby reducing the positive 'inventory pressure effect' on consumption. On the other hand, the higher promotion frequency may stimulate category consumption if the featured price cut entices consumers to buy a product they would not have bought otherwise. This may become stronger if consumers feel more certain that future promotions are likely (Sun 2005). Similarly, while the temporal spread of out-of-phase promotions may lower the need to buy large amounts, it may also inspire consumers to 'stock up till the next deal'. Whether out-of-phase calendars increase or decrease category expansion and stockpiling is an issue we empirically examine.[4]

2.2.3. Sales Volume Implications for the Manufacturer and the Retailer

How do these calendar differences play out for the different parties? For the manufacturer, net sales gains stem from brand (-store) switching and/or category expansion. The calendars affect these components in different ways. On the positive side, more out-of-phase schedules mean 'extra' brand-store switching, i.e. shifts away from rival brands at the

[4] To the extent that an out-of-phase calendar for the focal brand increases the likelihood that its promotion coincides with that of a rival brand in the focal chain, that calendar may lead to lower brand switching. Any such effect depends on the distribution of other brands' promotions – which we take up in the empirical part.

rival focal stores, in weeks where those stores do not promote. Moreover, in out-of-phase calendars, the focal brand is more often 'on promotion', which may stimulate consumption. On the negative side, frequent brand-promotions may stimulate buying in smaller quantities: this could reduce inventory pressure and consumption and, hence, brand sales. Taken together, the impact of calendar shifts on manufacturers' net sales gains depends on the relative size of the brand-store switching and consumption effects.[5]

For retailers, promotional gains should come from increased consumption or store switching. As argued above, more out-of-phase schedules can lead to higher or lower category expansion. As for the store-switching implications: each focal retailer will, during his promotion weeks, attract more customers of non-focal stores (i.e. stores that do not run promotions) under the out-of-phase schedule, because he does not have to 'split' this segment of customers with rival promoting chains. A caveat is that, while he will also attract more customers from competing *focal* chains in his own promotion weeks, he will lose customers when the brand is not promoted in his own store, but is promoted at a rival chain. The question for retailers is: how will this net out? Extant literature shows that the absolute sales shifts from promotions are asymmetric across brands and depend on their size and quality positioning (see, e.g., Neslin 2002). Similar forces may be at work for the competition between stores. On the one hand, retailers with many customers who buy in the category have more to lose from out-of-phase schedules, because they have more buyers that can switch away in weeks where rival stores promote. On the other hand, retailers with a large customer base (of not necessarily store-category loyal shoppers) may enjoy higher indirect store switching – consumers who visit the

[5]The higher promotion frequency may also leave less room for rival brands to eat into the promoted brand's sales (the 'deterrence' effect, see Lal 1990). Conversely, due to the spread in time, the brand's promotions in one focal chain, may coincide more with rival brands' promotions in the other (focal) chain, which may dampen their effect. The presence and strength of these effects depends on the frequency and timing of other brands' actions (that the manufacturer has no control of). Our analysis takes into account such other-brand promotion effects.

store for other purposes than buying the brand on promotion (Bucklin and Lattin 1992). Moreover, just like high-quality brands (Blattberg and Wisniewski 1989), high-end retailers may attract more customers through promotions than their lower-end rivals. Depending on which force prevails, larger or higher-end retailers may steal more (fewer) customers away from other focal chains in their own promotion weeks than they lose when those rivals promote – adding to (detracting from) the benefits of out-of-phase calendars.

2.2.4. Revenue Implications for the Manufacturer and the Retailer

So far, we focused on net volume gains. When it comes to net revenue (i.e. the dollar value instead of the volume of extra units sold), the trade-off between out-of-phase and in-phase schedules may be quite different. To the extent that out-of-phase calendars come with larger volumes sold on deal (i.e. at prices below the regular price), they become less appealing in terms of net revenue gains. For the manufacturer, (immediate and pre-emptive) store switching becomes a source of 'subsidization' (van Heerde et al. 2004, Foubert and Gijsbrechts 2010): consumers who would have bought the brand at full price, simply shift stores to benefit from the promotion. Moreover, the fact that brand promotions in more out-of-phase schedules are 'spread in time', may stimulate deal-to-deal buying, adding to the subsidization problem. For retailers, the lower prices also make out-of-phase schedules less attractive from a revenue perspective: extra unit sales (at deal prices) realized in feature weeks, being countered by (possibly asymmetric) sales losses at regular prices in weeks where competing retailers promote.

In the next section, we examine the magnitude of the performance difference between the calendars, based on consumer promotion responses in a real-life setting.

2.3. Methodology

2.3.1. Motivation

To empirically assess the impact of the promotion calendar, we need a methodology that properly captures consumers' promotional response. Three challenges emerge from the previous section. First, promotional sales gains/losses may accrue from shifts in consumers' category purchase incidence, brand- and store selection, and purchase quantity – hence, we need to model all four decisions. Second, the most rewarding calendar depends on the relative size of these shifts for specific brands and stores, which, in turn, depends on consumers' loyalty to these brands and stores. This calls for a flexible specification that accommodates heterogeneity in consumers' decision sequences, and in their brand and store preferences. Third, these shifts extend across multiple periods so we need to accommodate purchase dynamics. Treating such a setting analytically is prohibitive: as indicated by Freimer and Horsky: "The problem of several manufacturers and several retailers is currently an unsolvable problem even for the most stylized formulations" (Freimer and Horsky, 2008, p. 806). A complicating factor is that the decision authority of the different players is unknown: both manufacturers and retailers influence the calendar, but it is not clear in what way (Wierenga and Soethoudt 2009). Hence, following Chintagunta, Erdem, Rossi and Wedel (2006), instead of relying on analytical modeling, we adopt a more empirical approach. In the spirit of Silva-Risso et al. (1999) and Tellis and Zufryden (1995), we first estimate a 'full-fledged' model of consumers' response to observed promotion schedules. We then use this model as a tool to simulate and compare the effect of specific calendars.

2.3.2. Model Structure

To capture promotion response, we consider each shopping trip (*t*) of a household (*h*), and model the household's decision to buy a specific brand (*b*) in a given category (*c*) (or: to not buy from that category), at a given retailer (store) (*r*), and this in a specific quantity (*q*). We describe the choice decision (incidence, retailer and brand) first, and then consider purchase quantity.

Retailer, Category and Brand Selection. We adopt a utility-maximizing framework, in which the utility for household *h* of buying brand *b* from the considered category (we drop the category index to simplify notation) at retailer *r* is given by:

$$U_{brt}^{h} = Y_{brt}^{h} + \epsilon_{brt}^{h} = \beta^{h} X_{brt}^{h} + \epsilon_{brt}^{h} , \tag{2.1a}$$

where $\epsilon_{brt}^{h}$is a Gumbel-distributed random term, and Y_{brt}^{h} the systematic utility component. The latter is a function of (possibly household-specific) category-, retailer- and brand-related variables (including regular price and promotions), captured in the vector X_{brt}^{h}, with its associated parameter vector β^{h} (these variables are further specified below).

Similarly, the household's utility from visiting store *r* and not buying in the category is:

$$U_{0rt}^{h} = Y_{0rt}^{h} + \epsilon_{0rt}^{h} = \beta^{h} X_{0rt}^{h} + \epsilon_{0rt}^{h} , \tag{2.1b}$$

where, like before, ϵ_{0rt}^{h}, Y_{0rt}^{h} and X_{0rt}^{h} represent the Gumbel-distributed random component, the systematic utility component, and the vector of explanatory variables, respectively. As explained below, though X_{0rt}^{h} does not comprise brand-promotion variables directly, it does include variables that govern dynamic effects (e.g. consumption flexibility) and the potential for indirect store switching (e.g. store appeal in other categories) – see the section on operationalizations.

The way these utilities for the various retailers, brands, and no-purchase options translate into consumer choices, depends on the specification of the random components - in particular, the correlation of these components among the choice alternatives. In the marketing literature, the nested logit (NL) specification has been the dominant approach to capture an array of nested choices and their interrelationships (e.g. Gordon, Goldfarb and Li 2013). However, the NL model imposes one single correlation or 'nesting' structure, which, especially in a setting involving category, brand *and* retailer selection, may oversimplify consumers' actual decision structures. For instance: while Bucklin and Lattin (1992) use a store patronage, then category incidence 'hierarchy' in their NL model, Briesch, Dillon and Fox (2013) argue that category needs may 'drive' store choice. Or, while some consumers are willing to shop around for their favorite brand, brand selection also often takes place in-store (Campo, Gijsbrechts and Nisol 2000). Because the interplay between brand switching, store switching and category expansion is a key driver of promotion-calendar effects, we adopt a *generalized* nested logit (GNL) model here (e.g. Wen and Koppelman 2002).

For our setting, we propose a three nesting-structure GNL model, depicted in Figure 2.1. Given a category *c*, this GNL model specifies the probability that household *h* buys brand *b* from the category at retailer *r* (P_{brt}^{h}), or the probability that it visits retailer r but does not buy from the category (P_{0rt}^{h}), as a sum of three parts, each corresponding to a different decision structure (please see the probability expressions in Figure 2.1). In the first ('incidence→store→brand') structure, brands are grouped, or 'nested' within a retailer ('the retailer nest'), and retailers are nested within category-incidence options (purchase or no purchase). In the second ('incidence→brand→store') structure, retailers are nested within brands, which are nested within category purchases. The third structure, (‘store→incidence→brand’), nests brands within the category-purchase decisions, which are then nested within a retailer (see Figure 2.1).[6] In each structure, the substitution patterns between the different choice alternatives are governed by the nesting parameters (γ_{R1} and γ_{C1} in nesting structure 1, γ_{B2} and γ_{C2} in structure 2, γ_{R3} and γ_{C3} in structure 3). Like in the NL model, nesting parameters between zero and one, indicate that choice alternatives within the corresponding nest compete more strongly with one another than with other choice options. Conversely, nesting parameters above one imply that alternatives within a nest compete only weakly, and may even increase each other’s choice probability. If all nesting parameters equal 1, the GNL model reduces to a multinomial logit (MNL) specification.

--- Insert Figure 2.1 about here ---

A key advantage of the GNL model is that it accounts for the different routes along which an alternative can be selected, and for the differences in promotion response that these routes entail.[7] This is important because not all households have the same decision structure, and for a given household, decisions may come about differently at different points in time. The GNL model accommodates this by specifying the choice probability of a specific alternative (i.e. ‘buy a specific brand from the category at a given store’, or ‘visit a specific store without buying from the category’) as a mixture of the different routes or decision structures. The relative importance of the three routes is captured by the allocation parameters τ_i^h, i=1, 2, 3;

[6] Because we expect consumers to trade off brands *only* when they are in need of the category, we do not model sequences in which the category incidence decision comes after the brand choice decision. Put differently, we assume people do not decide which brand to buy when they do not purchase from the category.

[7] E.g., in the second structure (Figure 2.1: ‘incidence→brand→store’) with γ_{B2} and $\gamma_{C2} < 1$, retailers strongly compete for the purchases of a given brand once the consumer has decided on a category purchase, which leads to disproportionally more store switching for the promoted brand, and less category expansion. Also the level of the nesting parameters matters: if γ_{B2} were *larger* than one, retailers would compete disproportionally *less* for a given brand (making store switching a less predominant source of promotion response, and implying that brand promotions at one store may even leverage brand sales at other stores). Hence, different nesting structures and nesting parameters, place different weight on the sources of promo sales.

where $0 < \tau_i^h < 1$, and $\sum_i \tau_i^h = 1$.[8] If τ_i^h approaches 1 for a specific structure i, the household's choice probability is governed by that nesting structure alone, while intermediate levels of τ_i^h point to a mixture. In sum, the GNL model offers a parsimonious, yet flexible way to capture how households' category purchases of specific brands in specific stores, are affected by the brands' featured price cuts at these stores (which enter the systematic utility component).

Purchase quantity. Featured price cuts may also alter the quantity purchased for the chosen brand and store. Similar to previous authors (e.g. Ailawadi and Neslin 1998, Zhang and Krishnamurthi 2004), we define $Q_{brt}^{*,h}$ as a latent variable that determines how much a household wants to buy of the chosen brand from the category and retailer during a given shopping trip. Given that a category purchase occurs, and that brand *b* of retailer *r* is chosen, the observed quantity Q_{brt}^h is linked to this latent quantity as follows:

$$Q_{brt}^h = \begin{cases} {Q_{brt}^h}^* & \textit{if h purchases from the category, and chooses brand b from retailer r} \\ 0 & \textit{otherwise} \end{cases} \qquad (2.2a)$$

The latent quantity is itself a function of observed explanatory variables W_{brt}^h (see next section for details) - with parameter vector ϕ^h, and a normally distributed random component ξ_{brt}^h with mean 0 and standard deviation σ_ξ:

$${Q_{brt}^h}^* = \phi^h W_{brt}^h + \xi_{brt}^h. \qquad (2.2b)$$

Estimation

To ensure values for the allocation parameters τ_1, τ_2, and τ_3 within [0,1] and summing to 1, we estimate transformed parameters, η_1 and η_2, such that $\tau_1=\exp(\eta_1)/(\exp(\eta_1)+\exp(\eta_2)+1)$; $\tau_2=\exp(\eta_2)/(\exp(\eta_1)+\exp(\eta_2)+1)$ and $\tau_3=1-\tau_1-\tau_2$. To accommodate unobserved household heterogeneity, we adopt a random-effects approach and let the parameters of the utility drivers of category-brand-retailer choice and purchase quantity, and the (transformed) GNL allocation

[8] Although the summation to 1 is no strict requirement, it facilitates interpretation and is the dominant practice.

parameters, be normally distributed across households. We estimate the model using simulated maximum likelihood (Train 2009).

Because of its multiple, intertwined decision layers, estimation of the random-effects GNL model on our data presents several practical challenges. The model includes a large number of choice alternatives, and must be estimated on data involving all household trips to all stores – including separate observations for individual brand purchases and the no-purchase option. This not only drives up estimation time, it also causes numerical problems in the likelihood calculation (please see Appendix A for details). Moreover, such a dataset is unbalanced and sparse – the number of no-purchase observations largely outweighing the number of actual brand choices – which further compounds assessment of the brand-promotion effects. Previous studies solved this problem by using a sequential estimation approach (e.g. Gordon et al. 2013) and/or considering only a small subset of retailers or brands. Because (i) the GNL model has overlapping nests, and (ii) we need to be able to track brand-specific purchase shifts across all retailers and brands, over time, neither of these approaches is feasible in our setting. To tackle the issue, we proceed as follows. First, we estimate the parameters of the quantity and incidence-retailer-brand choice models separately. Clearly, category purchase incidence and quantity are likely to be related when driven by promotion, and this is captured in the systematic part of the incidence and quantity models – both of which include the promotion variables (see Table 2.3). Still, by estimating the GNL and quantity model separately, we assume that the unobserved components of these models are uncorrelated for reasons of tractability. Second, within the choice model, we disproportionately sample from the no-purchase and purchase trips, and then obtain the parameters using the Conditional ML estimation procedure discussed in Manski and McFadden (1981) and Cosslett (1981). Details on the GNL estimation are given in Appendix 2.A.

2.4. Data and Operationalizations

2.4.1. Data

We calibrate the models on GfK household panel data in four categories: beer, liquid laundry detergents, coffee and chips. These categories differ in the degree of storability, necessity, expensiveness and purchase frequency and, hence, in their promotional response (Bell, Chiang and Padmanabhan 1999). Consequently, they constitute a rich set to test of our calendar effects. Our data contain information on households' purchase histories, as well as weekly prices and feature activities for each brand and category, over 424 weeks, across all Dutch retail chains. We consider the top five retail chains in the Dutch market and a 'rest retailer' that comprises the remaining smaller chains. We retain only households that remain in the panel throughout the observation period (to avoid confounding calendar effects with household differences, see e.g. Geyskens, Gielens and Gijsbrechts 2010 for a similar approach[9]): these form the basis for our category-specific datasets. For each category, we then keep households with at least 2 category purchases, of which the last 10% purchases (rounded up to the next integer) are set aside for the holdout sample. The average number of purchases per household ranges from 15 (laundry detergents), over 51 (beer) and 63 (coffee), up to 86 (chips). Similar to, e.g., Geyskens et al. (2010) and Gielens (2012), we consider the top-selling brands in the category that account for at least 80% of total category purchases (or, if that calls for too many brands, include the top 5 national brands (NBs), and the private labels (PLs) with at least 5% of the store's category

[9] As pointed out in a review process of this paper, these households are possibly also more promotion-sensitive. However, because our main focus is on cross-calendar comparisons, rather than promotion effects per se, this is not a major problem here.

sales), and group the remaining brands in a ‘rest brand’ alternative. For one retailer, two (distinct) PLs account for a non-negligible portion of beer sales and, as such, are included as separate brands (PL1 and PL3 for beer).

--- Insert Table 2.1 about here ---

Table 2.1 presents descriptives on the chains’ and brands’ category shares (Panel A), along with their unit prices (mean and standard deviation, Panel B), for each of the four categories. In all categories, retailer 1 (R1) has the highest share, followed by R2; while R4 and R5 are smaller chains. The categories exhibit different levels of market share concentration (the leading brand covering over 50% of category sales in the chips and coffee categories, compared to about 20% for beer and laundry detergents) and private label share (almost 30% for coffee, compared to less than 5% for beer). Next to price differences between brands (e.g. in the beer category, NB5 is almost three times as expensive as R1’s economy private label, PL3) and retailers (R1 typically being higher priced), the table also points to price variation within brands and retailers over time. This already reveals the presence of promotional activity - something we turn to below.

2.4.2. Promotion Calendar: Descriptive Statistics

The brands’ price cuts that are featured in the retailers’ store flyer are focal to our analysis. Table 2.2 provides descriptives on the featured price cuts in the beer category (Figures for the other three categories yield similar patterns, and are provided in Appendix 2.B). Table 2.2, Panel A shows that the bulk of the feature promotions occurs for national brands. Among these NBs, featured price cuts are very popular: on average, inter-promotion times for a brand at a given retailer range between 5.5 weeks (NB1) and 11.32 weeks (NB5). The standard deviations of inter-promotion time indicate that the feature timing is quite irregular.

--- Insert Table 2.2 about here ---

For our purposes, the scheduling of the brands' promotions across retailers is elemental. Table 2.2, Panel B documents the patterns observed in the beer category (similar patterns are found for coffee, chips and laundry detergents – see Appendix 2.B). The table reveals that 34% of the featured price cuts occur at more than one retailer simultaneously. A breakdown by brand shows a similar pattern: the fraction of retailer-promotion weeks running concurrently at more than one retailer ranges between 27% (for NB4) and 40% (for NB1). Hence, though out-of-phase promotions appear to be more common, in-phase promotions do occur, and involve mostly the larger NBs (NB1 and NB2).

To further examine the observed patterns in promotion calendars, we correlated the week-to-week occurrence of featured price cuts among brands and retailers (as in Rao, Arjunji and Murthi 1995). While promotions of different brands within the same retailer do not seem related (e.g. for beer only two out of the 61 correlations are significant, one positive and one negative), we find slightly more significant correlations between the same brands across retailers (e.g. for beer: 4 out of 50 correlations, positive). To further explore this, we compared, for each national brand, (i) the actual percentage of weeks in the observation period in which it is promoted at two or more retailers simultaneously, to (ii) the percentage under random assignment (of its total retailer-promotion events across observation weeks). For each brand, the actual fraction of weeks with overlapping promotions (i.e. between 4.7% for NB4 and 11.1% for NB1) is lower than by chance (i.e. between 10.6% for NB4, and 28.3% for NB1). Finally, we conducted logistic regressions for each of the national brands at each of the top five chains, linking the presence (absence) of a promotion for the brand at the chain in a given week, to (i) the brand's promotion activity at the chain in that same week the year before, (ii) the brand's concurrent promotions at competing chains, (iii) same-week promotions of competing brands at the same and competing chains, and (iv) year fixed-effects. With only few coefficients significant, we do not find evidence of a 'set' pattern used by brands or retailers.[10]

In sum, these observations are consistent with anecdotal evidence that the (semi-)annual promotion calendar is the outcome of a negotiated agreement between the manufacturer and the retailer, in which (i) retailers often pressure the manufacturer not to promote at other retailers, while (ii) manufacturers may look for exclusivity in a given promotion period. Moreover, our exchanges with manufacturers indicate that they typically delegate negotiations to brand-account managers, whose interest is in optimizing the promotion calendar for their account rather than across stores. In all, this leads to observed diversity in the pattern of promotions – which will allow us to reliably estimate the impact of alternative schedules across retailers and their performance implications.

2.4.3. Variables and Operationalizations

To flexibly capture all relevant promotional effects, we include – next to the depth of the price cut $DiscDepth_{brt}$ – several variables related to the promoted brands' appearance in the retailer store flyers. Table 2.3 provides an overview of these variables and their operationalizations.

--- Insert Table 2.3 about here ---

Immediate effects are captured through a dummy $Promo_{brt}$, indicating a featured price cut for the brand at the retailer. We also incorporate the presence of such a promotion for the same brand at a different retailer, $Promo\_other_{brt}$: while the GNL model captures the overall patterns of brand-store competition, this term – in the spirit of Carpenter, Cooper, Hanssens and Midgley 1988 –

[10] E.g. for beer, with 2 out of 25 same-week last-year coefficients significant and positive, the results show that the promotion calendar is not simply transferred from last year. Moreover, focusing on within-brand cross-retailer promotions, we find the number of significant positive coefficients (8, pointing to likely concurrent actions) to almost equal the number of significant negative effects (9, indicating non-overlapping promotions across chains).

captures any additional cross-effects specifically due to the promotion activity. Moreover, we include an interaction term $Promo_{brt} * Weeks\_since\_last\_same^{h}_{brt}$, to capture the possibility that the longer the brand has not been on promotion at the chain, the more effective its promotion becomes. As dynamic variables, we further include a lagged promotion dummy $Promo_{brt-1}$ (to capture a post-promotion dip, van Heerde et al. 2004 or, conversely, a positive post-promotion effect reflecting consumer repeat purchases or inertia in the promotion implementation in-store, van Heerde, Leeflang and Wittink 2000), and (a main effect for) the number of weeks since the last feature promotion at any retailer (with household-specific retailer weights), $Weeks\_since\_last\_all^{h}_{brt}$. As advocated by Neslin and van Heerde (2009), the latter can capture a lead effect: consumers postponing their purchases in anticipation of the next promotion. Given the differences in brand inter-promotion times, we center this variable by subtracting the mean inter-promotion time for the brand in an initialization period (such that a positive value would suggest that, based on past experience, an offer for that brand is considered 'overdue'). Moreover, because anticipation effects will be weaker if the brand exhibited an irregular pattern in the past, we model the lead effect as a process function, influenced by the variance in inter-promotion time for that brand in an initialization period (see Table 2.3). In each category, the correlation table for the different promotion variables (see Appendix 2.C) does not point to overly high correlations (the highest correlation – between discount depth and the feature promotion dummy – ranges between .53 (laundry detergents) and .719 (beer), all other correlations are below .318) – suggesting that their separate impact can be assessed.

The promotion variables directly enter the utility associated with a specific brand-retailer choice and purchase quantity. Similar to previous models (e.g. Ailawadi and Neslin 1998, Fox, Montgomery and Lodish, 2004, Geyskens et al. 2010, Briesch, Chintagunta and Fox

2009), we add a number of controls to further capture category-, retailer- and brand-differences; as well as purchase dynamics. Category characteristics include seasonal variables, next to the household's category purchase rate (CR^h) and inventory ($Inventory_t^h$). The latter is defined as in Ailawadi and Neslin (1998), to capture the possibility of increased consumption due to inventory pressure (see Table 2.3). Retailer characteristics pertain to the considered category (i.e. whether the household's previous category purchase occurred in that store, $LastP\_Ret_{rt}^h$) as well as to the store overall (i.e. distance, $Dist_{rt}^h$; the retailer's initial share of household visits, $Ret\_Pref_r^h$; whether the store was visited on the previous trip, $LastV\_Ret_{rt}^h$; and the stores' overall appeal, which can be split into a fixed part (retailer dummies) and a variable part (Ret_Attr_{rt}) capturing the appeal of the promotion activities in categories other than the focal category). The latter reflect the chain's attractiveness to the consumer in general (i.e. for purchases other than the focal category), which, in turn, will drive the potential for indirect store switching. As for the brand-specific controls, these include, next to brand dummies and a brand state-dependence variable $LastP\_Brand_{bt}^h$, the regular unit price for the brand at the chain, $Price_{brt}$; and the size of the brand line carried by the retailer, $Assort_{brt}$. The last column of Table 2.3 indicates how these drivers enter equations (2.1a-2.1b) and (2.2b). Our random effects approach allows the retailer and brands' baseline and the slopes of all marketing mix variables (price, assortment, discount depth, and the promotions' immediate, lead, lag and cross-retailer effect) to follow a normal mixing distribution (see Table 2.4).

2.5. Estimation Results

Table 2.4 presents the fit statistics and estimation results (means and standard deviations of the mixing distributions) for the estimated models. The GNL model offers a significant improvement over an MNL specification (LR-test: p<.01). Moreover, in each category, the

GNL model points to a mixture of different nesting structures (allocation parameters in Table 2.4, Panel B, different from both zero and one), indicating that a simplified (nested logit) model would fail to fully capture households' decisions. Hit rates range between .295 and .303 in-sample, and between .270 and .290 for the holdout sample - satisfactory figures, considering the large number of choice alternatives (between 30 for coffee, and 47 for laundry detergents).

Turning to the model parameters, we find that the coefficients related to state dependence, initial household differences, and brand/store characteristics (e.g. distance, price, or assortment) all have face validity. To save space, we only discuss the promotion-related parameters (including those that govern the dynamics and the consumers' decision structure), and focus on the mean estimates (cross-household standard deviations are given in Table 2.4).

--- Insert Table 2.4 about here ---

In all categories, the presence of a featured price cut significantly enhances brand-retailer choice during the promotion week, as well as the quantity purchased ($p<.01$, except for laundry detergents, where the quantity effect is insignificant). The depth of the discount may further enhance the propensity to buy (beer and chips) or, if a purchase occurs, stimulate consumers to procure larger amounts ($p<.01$, beer and coffee). Concurrent promotions of the brand at another chain exert an 'extra' negative effect on the appeal of a brand-retailer combination, over and above the competitive interplay inherent in the GNL structure, for beer ($p<.01$). Interestingly, they create positive spillovers for coffee and chips ($p<.01$) – possibly because the feature ads 'remind' consumers to buy these products in their usual store (Anderson and Simester 2013).

Turning to the dynamic effects, larger inventories reduce consumers' propensity to buy ($p<.01$, beer, laundry detergents and chips) or amount purchased ($p<.01$, coffee). Whereas negative inventory-variable effects pertain to all brands and retailers, the lagged promotion coefficient indicates to what extent post-promotion effects differ between the previously promoted retailer-brand, and others, in the week following the first promotion. This coefficient is negative for coffee – suggesting that having bought a specific brand on deal at a given chain, especially reduces the purchase rate for that brand and chain in the week after. It is significantly positive for laundry detergents (incidence) and beer (incidence and quantity). This may follow from inertia in the promotion implementation (van Heerde et al. 2004), or point to 'momentum' – the recent promotion temporarily making the brand-retailer the more likely option-of-choice.

We do not find a positive interaction between promotion effectiveness and weeks since the last brand promotion at the same store. This suggests that, within the data range, low promotion frequency of a brand *within a chain* does not enhance its impact. In contrast, brand promotions at retailers where they have not been on deal for long, appear *less* effective. One explanation is that consumers are less alert to promotions by these brands at these chains, and less likely to organize their purchases around these promotion events.[11] In the same spirit, we do obtain lead effects (as evidenced by the main effects of weeks since promotions at any retailer, and its interaction with the brand's promotion regularity) for coffee and chips: consumers being less likely to buy the brand if they believe a promotion is due, especially if there is high regularity in the brand's promotion schedule (as the process function in Table 2.3 indicates, a positive coefficient of the standard deviation of inter-promotion time, implies that more regular promotions enhance the anticipation effect). The consumption flexibility parameter is highest for laundry detergents, followed by coffee, beer and chips. Given that a more positive (negative)

[11] Another explanation is that brands that promote infrequently do so because they know their promotions are less effective. We thank the editor for pointing this out.

parameter for consumption flexibility points to less (more) flexible consumption (Ailawadi and Neslin 1998, see also Table 2.3), these results make intuitive sense.

The routes along which these utility drivers affect consumers' choices are shown in Table 2.4, Panel B, which reports the relative importance of the three decision sequences (as reflected in the allocation parameters), and the implied competitive patterns (as reflected in the nesting parameters). Interestingly, among the wide range of possible decision patterns accommodated by the GNL model in Figure 2.1, only four main patterns emerge across the different categories – as described in Figure 2.2. These decision patterns are characterized by a sequence, combined with a level of the higher and lower nesting parameter (each of which can be equal to, higher than, or lower than 1, see also footnote 7). For each category, a mixture of these patterns is at work, but with different degrees of importance – which is not surprising, given the different category characteristics (which we further explore below).

--- Insert Figure 2.2 about here ---

The mean estimates of the allocation parameters show that in the beer category, Pattern B is predominant (82%), with some influence of Pattern A (17%). The opposite holds for laundry detergents (Pattern A (60%), Pattern B (34%)). For coffee, Patterns A (38%) and D (37%) dominate, while the chips category exhibits a mixture of Patterns A (60%), C (16%) and D (24%). To explore whether these mixtures only reflect differences in choice strategies *between* households, or also imply that a given household may 'switch' strategies *across purchase occasions*, we consider the household-specific posterior estimates of the allocation parameters (We obtain these posteriors following the procedure described in Train 2009, p. 266). In the beer category, all households primarily stick to Pattern B, with some occasional switching to Pattern A. In the remaining three categories, individual households, rather than being ‘assigned’ to one choice pattern, typically exhibit a mixture of strategies across their category purchase trips (Details are available upon request).

In sum, it appears that, across categories, the promotion effects materialize through a different mixture of these main routes, both across and within households, with different propensities for category expansion\stockpiling, store switching, and brand-store switching. How this shapes the impact of alternative calendars is something we turn to below.

2.6. Implications

2.6.1. Simulation Setup

To assess the effects of different promotion calendars, we use our estimates as inputs for simulations on the actual data involving a 26-week period (and promotion calendars, at all brands and retailers, in this period) as a backdrop. Such a half-yearly scenario corresponds to the typical calendar-planning horizon in practice. We consider changes in the calendar of featured price cuts for the leading brand, at two retailers (the leading chain in the category and the runner-up), with promotions for other brands (at any chain) at their actual level. Shifting the brand calendar at only two chains makes it easier to trace the underlying mechanisms and – given that concurrent promotions often occur at two chains (see Table 2.2 and Appendix 2.B) – is realistic. The number of feature promotions at the two retailers is set roughly equal to the actual total in the observation period, and then equally split between the chains. Each feature lasts one week, with a price cut equal to the brand’s actual mean discount at the two chains. Appendix 2.D provides an overview of the simulation setup.

To realistically assess the calendar effects and avoid the Lucas critique (van Heerde, Dekimpe and Putsis 2005), we consider schedules that fall within the data range. In the out-of-phase schedule, none of the brand promotions concurrently run at the two retailers. Such a calendar is actually observed in a number of (half-year) planning periods. For the in-phase schedule, we let two-thirds of the promotion events coincide at the two retailers – the maximum 'simultaneity' in the dataset over 26 consecutive weeks. The remaining one-third still takes place at the two retailers in different weeks (along with any other-brand promotions, which are kept common across the two scenarios). We then compare the results across the two calendars (fully out-of-phase vs. two-thirds in-phase/one-third out-of-phase, or simply: out-of-phase vs. in-phase hereafter), and with the benchmark setting of no featured price cuts for the brand at the two retailers. To distinguish idiosyncratic sequencing and contemporaneous effects from systematic calendar-type effects, we verify these effects for different implementations within each calendar type (see Appendix 2.D).

2.6.2. Simulation Results

Figure 2.3 reports, for each promotion calendar: (i) the gross sales lift (i.e. volume increase over the baseline during promotion weeks, Panel A), (ii) the net volume gain (obtained as sales volume in units under the promotion calendar across the 26 weeks[12], minus the baseline volume for that same period, Panel B), and (iii) the net revenue gain (calculated as the net volume gain minus the discount fraction (i.e. 0.25) times the total brand volume sold under promotional conditions (= baseline + gross sales lift), Panel C). It provides these figures for the manufacturer (brand) and the two retailers (category) in absolute terms, and also reports the % differences between calendars (relative to the in-phase calendar).

In all categories, both calendars lead to substantial gross sales lifts and significant net volume and revenue gains compared to the benchmark setting, for all parties involved. The size

[12] Because of differences in seasonality, the absolute promotion effects obtained in our 26-week period may not generalize to the remaining 26 weeks of the year. However, because we are mainly interested in the differences between calendars, and we compare calendars for the same period, this is not a key problem here. Also note that the correlations between the promotion variables and seasonal variables are very low (below .05 in absolute value), indicating that the promotion calendar itself does not systematically differ across the 26-week periods.

of the gross sales lift relative to the baseline ranges from 169% (chips) to 244% (laundry detergents). These figures are comparable to extant findings (Ailawadi et al. 2006) and support the face validity of the results.

--- Insert Figure 2.3 about here ---

Gross Sales Lift. Zooming in on the calendar *differences* in gross sales lift first, we observe a mixed pattern of effects across categories. For laundry detergents and chips, the number of extra units sold on deal is the same for both calendars (p>.10). For beer and coffee, Figure 2.3 shows that out-of-phase calendars lead to significantly higher gross sales lifts, for the manufacturer and both retailers: on average, alternating schedules yield between 6.8% and 17.9% larger immediate sales bumps than their in-phase counterparts.

Net Volume Gains. The picture changes when it comes to net volume gains. In the beer and coffee category, out-of-phase calendars no longer entail higher *incremental* sales volume for the manufacturer (p>.10). Retailers continue to enjoy higher net volume in the out-of-phase schedule for beer and coffee (p<.05). However, though the % difference between calendars remains important (4.7% to 12.1%, see Figure 2.3, Panel B), the absolute gains are now more modest. In the laundry detergents and chips categories, the promotion timing does not affect the retailers' net volume gains (p>.10). In contrast, for chips, the out-of-phase calendar leads to higher incremental brand volume (6.35% higher than in-phase), with absolute differences that are strongly significant (p<.01). So, even if this is not apparent from the gross sales lift, manufacturers do incur a net sales gain from promoting out-of-phase in this category.

Net Revenue Gains. Because the gross sales lift (and, hence, the amount of subsidization) does not significantly differ between the calendars for laundry detergents and chips, moving from net volume (Panel B) to net revenue gains (Panel C) does not change our findings. In laundry detergents, all parties continue to be indifferent to the promotion calendar ($p>.10$). For chips, the manufacturer continues to enjoy a (modest) absolute performance increase from promoting out-of-phase. In the beer and coffee category, where the sales bump is calendar-specific, the volume and revenue implications are somewhat different. For the *manufacturer*, the net revenue gain under in-phase promotions exceeds that of out-of-phase schedules, and significantly so for coffee ($p<.01$). For *retailers,* though the % differences between calendars remain sizable, the calendar differences become smaller in absolute terms.

Sources. Where do these differences come from? Comparing the calendars' category sales across all chains throughout the 26-week period, we find that, though the out-of-phase schedule leads to *category expansion* for coffee ($p<.05$) and chips ($p<.01$), the effect is very modest (.1% to .2%), and we do not observe it for beer or laundry detergents. As such, calendar effects seem to primarily stem from differences in (brand-) store switching. To further explore this, we consider a breakdown of the promotion bump by comparing, for each household, the purchases under the simulated promotion calendars, to those in a benchmark setting without promotions for the brand at the two chains (see Appendix 2.D for details).

--- Insert Figure 2.4 about here ---

Figure 2.4 shows the sales shifts underlying the promotion calendars, for each category. For laundry detergents, there are no systematic calendar differences in the sales bump components. This is no surprise: as the model estimates reveal, consumption in this category is inflexible, and competition primarily occurs among brands within the store (Pattern A). For beer and coffee, out-of-phase promotions only trigger more store switching than in-phase schedules ($p<.05$) – which could stem from Patterns B and D, respectively. This explains the absence of a net volume gain for the manufacturer: the higher gross sales lift at the promoting retailer in the out-of-phase schedule, comes at the expense of brand sales in other stores. The picture is very different for chips, where the out-of-phase calendar implies more brand switching ($p<.01$), and a significantly higher sales lift at non-promoting stores (negative difference for store switching in Figure 2.4, $p<.10$). A tentative explanation can, again, be found in the model estimates: promotions for chips do not warrant shifts toward the promoting stores,[13] yet, they lead to significant positive 'cross-store spillover' effects for the brand even in stores where it is not on deal (decision Pattern C, reinforced by a positive coefficient for 'promo at other stores' in Table 2.4). Out-of-phase calendars, which imply more promotion weeks, may thus benefit the manufacturer: whenever the brand is on deal, this raises attention to the brand at all stores, and triggers extra brand purchases.

Robustness checks. To check the generalizability of the findings, we replicate the simulations for a scenario with the leading and a smaller (lower-end) retailer. The outcomes are largely similar, with significant retailer effects for beer and coffee (the results are reported in Appendix 2.D). To explore asymmetries between the two chains, we isolate store shifts at the expense of the rival promoting store versus other stores. We find that the larger retailer enjoys lower sales shifts at the expense of the smaller store, than vice versa. At the same time, the large retailer reaps more sales from other stores than its smaller adversary, possibly because, being a larger (higher-end) player, its feature ads are more visible (attractive), or it has more potential for indirect store switching. In sum, promoting out-of-phase allows (both small and large) retailers to draw more sales away from rival stores, and entails (albeit modest) net volume gains.

[13] Though Pattern D, to some extent, also occurs for chips (Table 2.4, Panel B), the 'last purchase' and 'last visit' coefficients for this category are high (consumers being inclined to buy chips in the same store), which dampens the store switching effects.

2.7. Discussion, Limitations and Future Research

2.7.1. Discussion

Our results show that promotion calendars lead to notable performance differences in categories where promotions drive the brand's purchase-location-of-choice, either in the form of direct store switching (as is the case for destination categories, like beer), or indirect store switching (consumers shifting the category purchase to a store already visited for other purposes – a pattern observed for coffee). In such categories, out-of-phase calendars lead to much higher volume bumps in promotion weeks. However, when it comes to *net* volume gains, we show that in these categories, manufacturers no longer benefit from out-of-phase calendars. Retailers continue to incur higher net volume from alternating promotions, but the gains turn out to be more modest. This shift is reinforced when it comes to net revenue. Because a larger portion of sales in the out-of-phase calendars occurs at deal prices, the average revenue per unit sold further drops. It follows that, even if out-of-phase promotions have intuitively appeal because of the larger gross sales lifts, promoting out-of-sync leads to only small net revenue gains for retailers, and actually lowers them for manufacturers.

In 'non-destination' categories (in which a brand promotion typically does not warrant a store shift), out-of-phase calendars do not trigger more store switching than in-phase schedules, and hardly alter retailer performance. Interestingly, our chips results suggest that in such categories, calendars may still matter for the manufacturer, but for different reasons. This happens if brand promotions in one chain create positive spillovers for (the brand in) rival chains (where the brand is not on deal) – a phenomenon recently documented by Anderson and Simester (2013) that seems to be at work in the chips category. For the manufacturer alternating schedules thus seem to create more weeks in which the featured price cut attracts attention to the brand and, with positive chain spillovers, trigger more brand switching at any store. Of course, because it is based on only one category, this reasoning is still speculative, and needs to be verified in other categories.

Our results have several implications for managers. First, we show that though promotion calendars may matter, the presence and direction of their effects depend on the consumers' dominant decision processes for the category. The question is: what drives these processes, and can managers anticipate them? To explore this, and further check the validity of our estimated decision processes, we tie them with category factors collected by Steenkamp, Geyskens, Gielens and Koll (2004), through a survey on 62 categories among a representative sample of Dutch consumers[14]. The categories where our calendar differences are most pronounced (i.e. where out-of-phase schedules lead to higher gross sales lift for each party, and higher net gains for the retailers – beer and coffee) – have below-average category-specific store loyalty and impulse buying, yet rather high performance risk[15]. In contrast, laundry detergents and chips are marked as categories in which the consumer does not shop around for his favorite brand (high store loyalty and low performance risk). This makes the calendar decision quite inconsequential for retailers. For items that score high on 'impulsiveness' like chips, though, having seen a store flyer ad may act as a purchase trigger upon encountering the brand in-store (even if that is a store where the brand is not on deal), and out-of-phase calendars may benefit the manufacturer.

Second, we find that immediate sales shifts are a poor indicator of which calendar yields the highest net gains. In settings where out-of-phase calendars lead to substantially more sales on deal, they end up generating about the same (for retailers) or lower (for manufacturers) net

[14] We thank the authors for making these data available.
[15] Details available on request.

revenue gains than in-phase schedules. Conversely, settings with similar gross sales lift may hide net revenue gains for the manufacturer under the out-of-phase regime. Hence, practitioners interested in their bottom line, should not be (mis)guided by calendar differences *within* the promotion period.

Third, our results cast doubt on the prevailing view that retailers are better off promoting out-of-phase. We show that striving for out-of-phase brand promotions with rival chains does not necessarily boost retailers' net revenue gains, even in categories where brand promotions influence the purchase-location-of-choice. Because in such categories retailers often grant high levels of pass through, the *profit* implications of out-of-phase calendars may actually be worse. For instance, in the beer category, traditionally considered a 'traffic builder', Besanko, Dube and Gupta (2005) report pass-through levels of over 500%. With regular retailer beer margins of about 18% (Besanko et al. 2005), this would imply lower simulated profits from out-of-phase than in-phase calendars, for both retailers.

Still, to the extent that out-of-phase calendars generate additional traffic for the retailer, they may imply more cross-category sales (halo effects) to compensate the category losses. To explore this issue, we compared the number of store visits in our simulations under the two calendars. We find that, even in categories where alternating promotions lead to more *category* purchase shifts across stores (beer and coffee), *traffic* to the two stores across the planning period hardly increases (i.e. 0.1% of total visits). This suggests that much of the store switching is indirect – consumers shifting category purchases among stores they would have visited anyway – and extra cross-shopping probably limited. It follows that even if retailers are in a position to negotiate out-of-phase calendars, they may not have an incentive to do so in the first place.

Finally, we find that with net volume gains as the performance metric, manufacturer and retailer interests are not incongruent. In categories where featured price cuts produce shifts in category (brand) sales to the promoting store, retailers may prefer out-of-phase schedules, while manufacturers are indifferent. Conversely, if featured price cuts primarily generate attention to the brand (at any store) to the detriment of rival brands, manufacturers may prefer out-of-phase promotions, while retailers do not care. These insights suggest that, when it comes to promotion calendar negotiations, the interests of both parties are not necessarily unaligned.

2.7.2. Limitations and Future Research

Clearly, our study has limitations that set the stage for further research. First, our empirical analysis pertained to only one country, and consumers' propensity to switch brands/stores may be different in other settings. Second, we focused on outcomes for the promoted brand (for the manufacturer) and category (for the retailer), and it would be interesting to study cross-brand and cross-category effects. Given that halo effects are typically small (Ailawadi et al.'s 2006), and that out-of-phase schedules do not seem to substantially increase traffic over the planning period, we do not expect them to change calendar preferences - something future studies could verify. Third, while we considered the brand as a whole, consumers' inclination to switch stores may vary with the promoted SKUs (e.g. package size or type), and our study sets the stage for an analysis of SKU level-calendars. Fourth, we studied price cuts featured in the retailers' store flyer – which, being visible to consumers outside the store, are most prone to trigger store switching. Still, it may be useful to analyze how the scheduling of *in-store promotions* across retailers plays out for different parties. Fifth, while we documented sales volume and revenue implications, managers may ultimately be more interested in profit – which we could only roughly reflect on, for lack of data. With per-unit promotional funding and retailer pass-through below one, manufacturers are likely to profit more from in-phase calendars. At the same time, such calendars may lead to higher sales volatility, rendering the logistics more complex and costly (see, e.g., Cachon, Randall and Schmidt 2007). These are interesting topics for future study. Sixth, our analysis used the perspective of a leading national brand, and it would be interesting to check whether similar patterns can be found for all brands. Finally, we empirically documented the implications of moving towards a more in-phase calendar *for a given brand*, against the backdrop of rival brand promotions, which we kept constant. Because (i) we considered *gradual* calendar changes, within the boundaries of the data and (ii) in line with extant findings (Steenkamp, Nijs, Hanssens and Dekimpe 2005), we did not find any clear pattern of competitive reactions in our data, this approach seems justified. Still, more radical calendar changes may cause rivals to follow suit, and call for a structural analysis of the calendar effects – which we leave as a topic for future study.

Figure 2.1: GNL Model for Joint Brand-Choice, Store-Choice and Category Purchase Incidence Decision

	Nesting Structure		
	1: Incidence→ Store→ Brand	2: Incidence→ Brand→ Store	3: Store→ Incidence→ Brand
$P^h_{brt} =$	$P^{h,1}_{brt\mid .ri} * P^{h,1}_{.rt\mid ..i} * P^{h,1}_{it} +$	$P^{h,2}_{brt\mid b.i} * P^{h,2}_{b.t\mid ..i} * P^{h,2}_{it} +$	$P^{h,3}_{brt\mid .ri} * P^{h,3}_{brt\mid .r.} * P^{h,3}_{rt}$
$=$	$\frac{(\tau1^h * e^{(Y^h_{brt})})^{\frac{1}{\gamma_{R1}}}}{\sum_j\left(\tau1^h * e^{(Y^h_{jrt})}\right)^{\frac{1}{\gamma_{R1}}}} * \frac{\left(\sum_j\left(\tau1^h * e^{(Y^h_{jrt})}\right)^{\frac{1}{\gamma_{R1}}}\right)^{\frac{\gamma_{R1}}{\gamma_{C1}}}}{\sum_s\left(\sum_j\left(\tau1^h * e^{(Y^h_{jst})}\right)^{\frac{1}{\gamma_{R1}}}\right)^{\frac{\gamma_{R1}}{\gamma_{C1}}}} * \frac{\left(\sum_s\left(\sum_j\left(\tau1^h * e^{(Y^h_{jst})}\right)^{\frac{1}{\gamma_{R1}}}\right)^{\frac{\gamma_{R1}}{\gamma_{C1}}}\right)^{\gamma_{C1}}}{(D1^h_t+D2^h_t+D3^h_t)} +$	$\frac{(\tau2^h * e^{(Y^h_{brt})})^{\frac{1}{\gamma_{B2}}}}{\sum_s\left(\tau2^h * e^{(Y^h_{bst})}\right)^{\frac{1}{\gamma_{B2}}}} * \frac{\left(\sum_s\left(\tau2^h * e^{(Y^h_{bst})}\right)^{\frac{1}{\gamma_{B2}}}\right)^{\frac{\gamma_{B2}}{\gamma_{C2}}}}{\sum_j\left(\sum_s\left(\tau2^h * e^{(Y^h_{bst})}\right)^{\frac{1}{\gamma_{B2}}}\right)^{\frac{\gamma_{B2}}{\gamma_{C2}}}} * \frac{\left(\sum_j\left(\sum_s\left(\tau2^h * e^{(Y^h_{bst})}\right)^{\frac{1}{\gamma_{B2}}}\right)^{\frac{\gamma_{B2}}{\gamma_{C2}}}\right)^{\gamma_{C2}}}{(D1^h_t+D2^h_t+D3^h_t)} +$	$\frac{(\tau3^h * e^{(Y^h_{brt})})^{\frac{1}{\gamma_{R3}}}}{\sum_j\left(\tau3^h * e^{(Y^h_{jrt})}\right)^{\frac{1}{\gamma_{R3}}}} * \frac{\left(\sum_j\left(\tau3^h * e^{(Y^h_{jrt})}\right)^{\frac{1}{\gamma_{R3}}}\right)^{\frac{\gamma_{R3}}{\gamma_{C3}}}}{\left(\sum_j\left(\tau3^h * e^{(Y^h_{jrt})}\right)^{\frac{1}{\gamma_{R3}}}\right)^{\frac{\gamma_{R3}}{\gamma_{C3}}} + (\tau3^h * e^{(Y^h_{0rt})})^{\frac{1}{\gamma_{C3}}}} * \frac{\left(\left(\sum_j\left(\tau3^h * e^{(Y^h_{jrt})}\right)^{\frac{1}{\gamma_{R3}}}\right)^{\frac{\gamma_{R3}}{\gamma_{C3}}} + (\tau3^h * e^{(Y^h_{0rt})})^{\frac{1}{\gamma_{C3}}}\right)^{\gamma_{C3}}}{(D1^h_t+D2^h_t+D3^h_t)}$
$P^h_{0rt} =$	$P^{h,1}_{0rt\mid ..i} * P^{h,1}_{0t} +$	$P^{h,2}_{0rt\mid ..i} * P^{h,2}_{0t} +$	$P^{h,3}_{0rt\mid .r.} * P^{h,3}_{rt}$
$=$	$\frac{(\tau1^h * e^{(Y^h_{0rt})})^{\frac{1}{\gamma_{C1}}}}{\sum_s (\tau1^h * e^{(Y^h_{0st})})^{\frac{1}{\gamma_{C1}}}} * \frac{(\sum_{r=1}^{R}(\tau1^h * e^{(Y^h_{0rt})})^{\frac{1}{\gamma_{C1}}})^{\gamma_{C1}}}{(D1^h_t+D2^h_t+D3^h_t)} +$	$\frac{(\tau2^h * e^{(Y^h_{0rt})})^{\frac{1}{\gamma_{B2}}}}{\sum_r (\tau2^h * e^{(Y^h_{0rt})})^{\frac{1}{\gamma_{B2}}}} * \frac{\left[\sum_r (\tau2^h * e^{(Y^h_{0rt})})^{\frac{1}{\gamma_{B2}}}\right]^{\gamma_{B2}}}{(D1^h_t+D2^h_t+D3^h_t)} +$	$\frac{\left((\tau3^h * e^{(Y^h_{0rt})}\right)^{\frac{1}{\gamma_{C3}}}}{\left(\sum_b\left((\tau3^h * e^{(Y^h_{brt})}\right)^{\frac{1}{\gamma_{R3}}}\right)^{\frac{\gamma_{R3}}{\gamma_{C3}}} + \left((\tau3^h * e^{(Y^h_{0rt})}\right)^{\frac{1}{\gamma_{C3}}}} * \frac{\left(\left(\sum_b\left(\tau3^h * e^{(Y^h_{brt})}\right)^{\frac{1}{\gamma_{R3}}}\right)^{\frac{\gamma_{R3}}{\gamma_{C3}}} + \left(\tau3^h * e^{(Y^h_{0rt})}\right)^{\frac{1}{\gamma_{C3}}}\right)^{\gamma_{C3}}}{(D1^h_t + D2^h_t + D3^h_t)}$
with	$D1^h_t = \left(\sum_r\left(\sum_j\left(\tau1^h * e^{(Y^h_{brt})}\right)^{\frac{1}{\gamma_{R1}}}\right)^{\frac{\gamma_{R1}}{\gamma_{C1}}}\right)^{\gamma_{C1}} + \left(\sum_r \left(\tau1^h * e^{(Y^h_{0rt})}\right)^{\frac{1}{\gamma_{C1}}}\right)^{\gamma_{C1}}$	$D2^h_t = \left(\sum_b\left(\sum_r\left(\tau2^h * e^{(Y_{b,r})}\right)^{\frac{1}{\gamma_{B2}}}\right)^{\frac{\gamma_{B2}}{\gamma_{C2}}}\right)^{\gamma_{C2}} + \left(\sum_r \left(\tau2^h * e^{(Y^h_{0rt})}\right)^{\frac{1}{\gamma_{B2}}}\right)^{\gamma_{B2}}$	$D3^h_t = \sum_r\left[\left(\sum_j\left(\tau3^h * e^{(Y^h_{jrt})}\right)^{\frac{1}{\gamma_{R3}}}\right)^{\frac{\gamma_{R3}}{\gamma_{C3}}} + \left(\tau3^h * e^{(Y^h_{0rt})}\right)^{\frac{1}{\gamma_{C3}}}\right]^{\gamma_{C3}}$

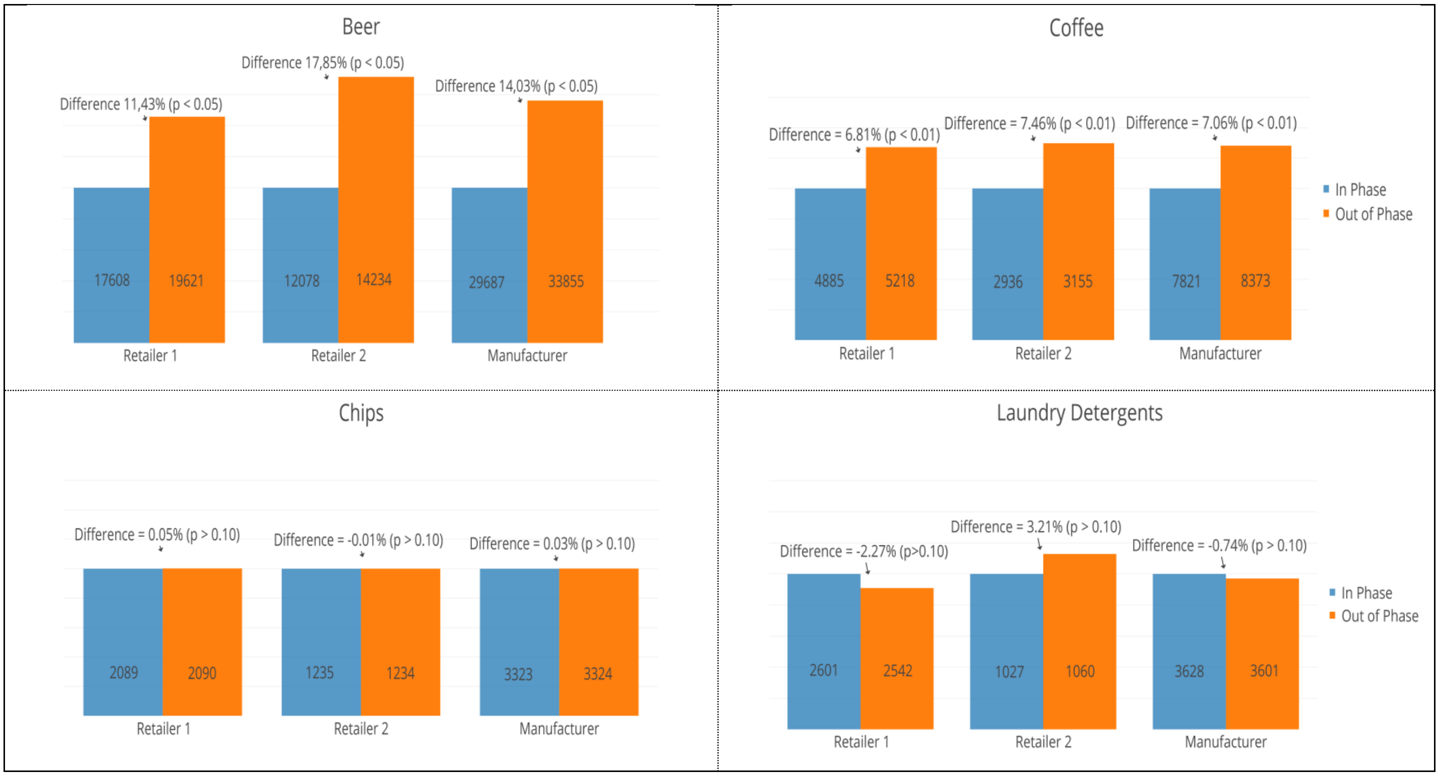
Figure 2.2: Main Decision Patterns in the Estimated GNL Model

Pattern[a]	Characteristics[b]
A: 'Incidence→Store→Brand' $\gamma_{R1} <1$, $\gamma_{C1} \sim=1$	• Strong competition among brands within a store • Category purchase depends on stores' attractiveness in the category as a whole
B: 'Incidence→Brand→Store' $\gamma_{B2} <1$, $\gamma_{C2} < 1$	• Consumers are brand-loyal with high (possibly direct) store-switching • Category incidence is need-based (brands strongly compete for a category purchase)
C: 'Incidence→Brand→Store' $\gamma_{B2} \geq 1$, $\gamma_{C2} >1$	• Increased brand appeal at one store (e.g. through promotions) may spill over to other stores • Enhanced appeal for one brand may increase category incidence overall (including other-brand purchases)
D: 'Store→Incidence→Brand' $\gamma_{R3}<1$, $\gamma_{C3} >1$	• Attractiveness of the focal category enhances overall store appeal (which may lead to direct and indirect store switching) • Brand compete heavily within store for a category purchase

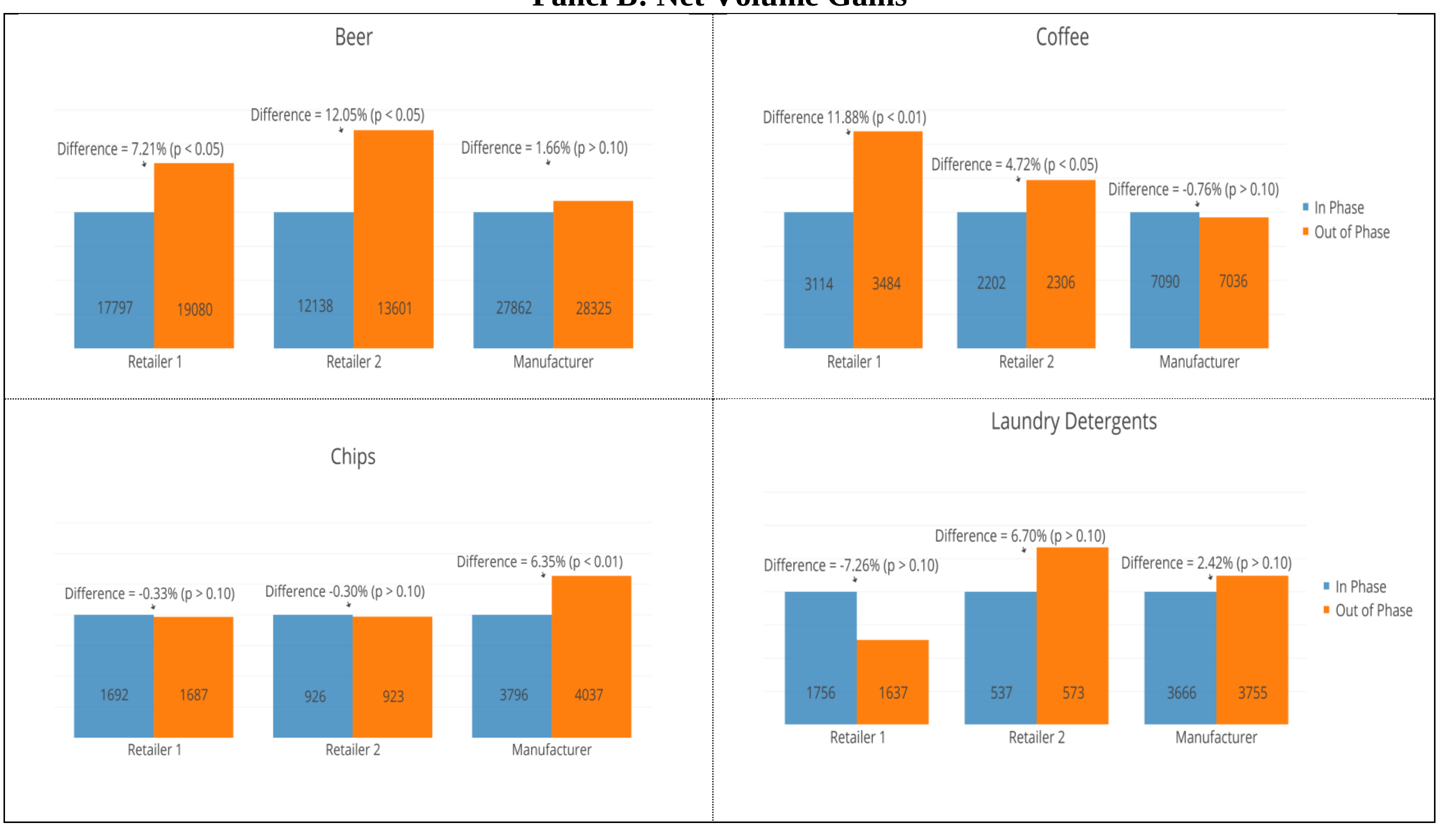
[a] See Figure 2.1 for the GNL model structure. [b] Note that, as indicated in the methodology section, a nesting parameter below 1 implies disproportionally high competition within the corresponding nest, while a parameter above 1 implies disproportionally low competition or even leverage effects.

Figure 2.3: Simulation Results

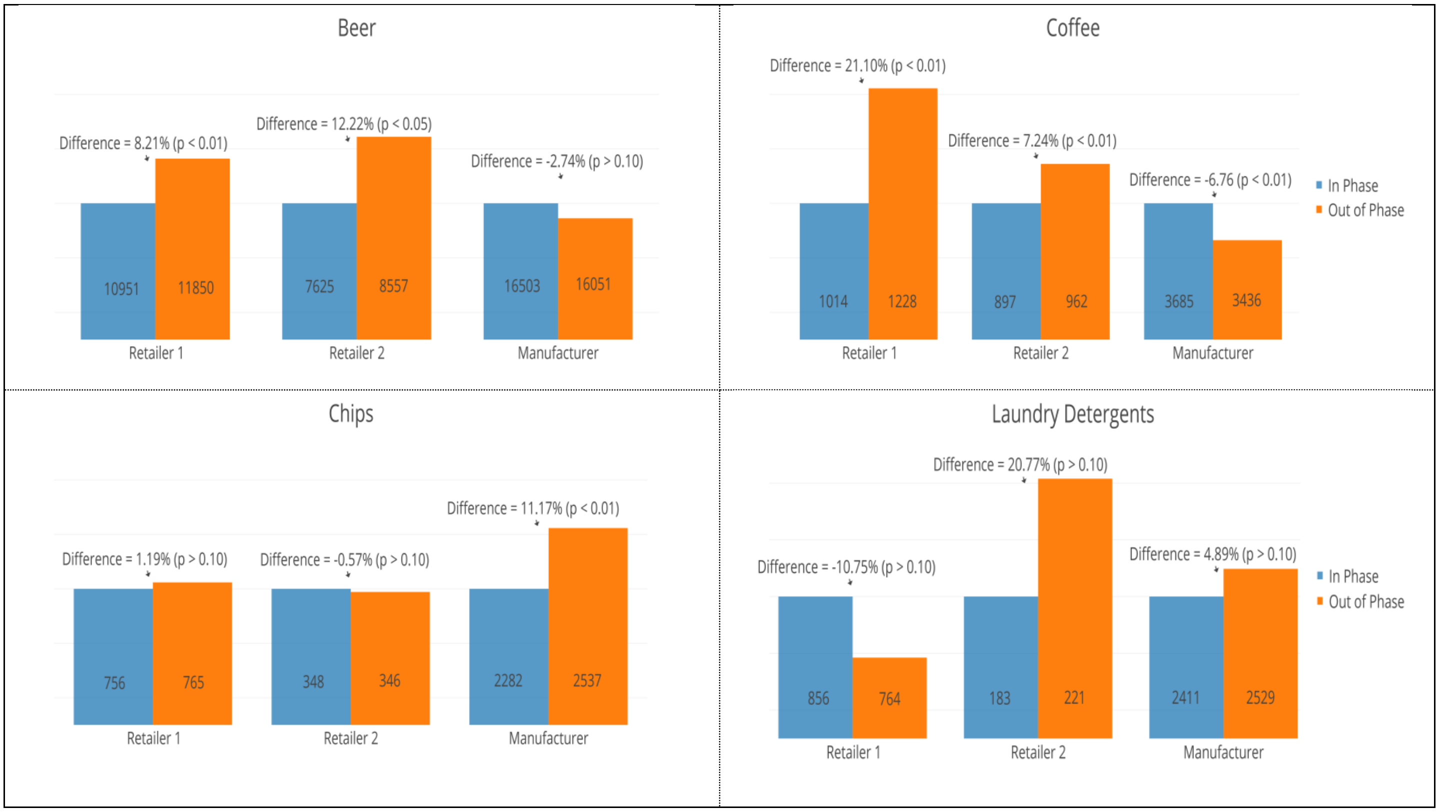
Panel A: Gross Sales Lift



Panel B: Net Volume Gains

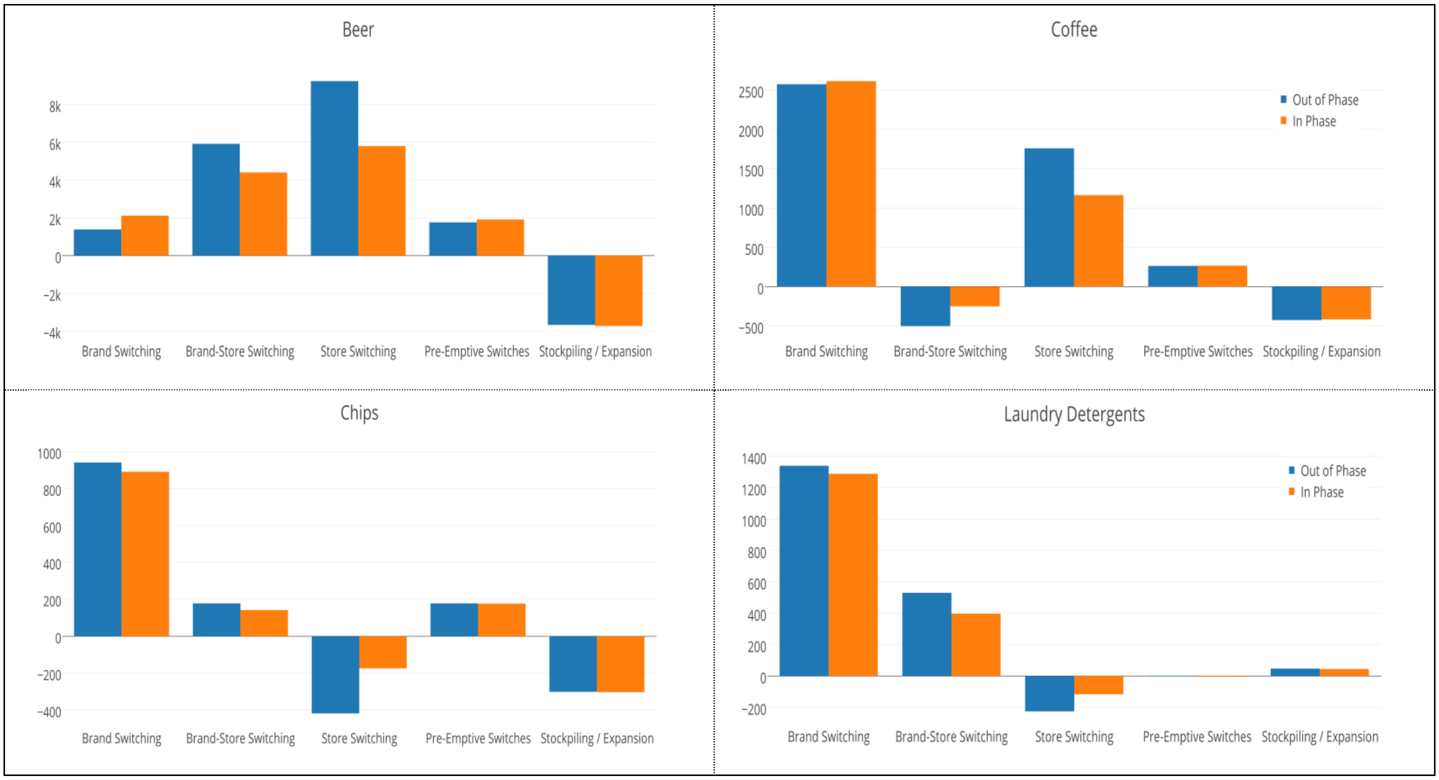


Panel C: Net Revenue Gains



Notes: Calendar differences are calculated as Out-of-Phase minus In-Phase, divided by In-Phase. Significances based on 100 simulations. Measures are calculated over the 26 week period for the retailers and manufacturer. For the retailer, the figures pertain to the whole category (all brands), for the manufacturer they pertain to the brand (at all retailers).

Figure 2.4: Sources of the Promotional Sales Bump



Notes: For each calendar, the 'bars' are calculated as (i) the difference in sales between the no-promotion benchmark scenario (baseline) and the considered calendar, (ii) across the two retailers, (iii) during the promotion weeks (for brand-switching, brand-store switching and store-switching) or in the week following those promotions (for pre-emptive switches – including pre-emptive brand-, store-, and brand-store switches – and stockpiling). For instance, '*brand-switching*' is the baseline sales minus calendar sales (totaled across promotion weeks and the two retailers) for *rival brands within the promoting store* (such that a 'positive' number means that rival brands in the same store lose when the focal brand is on promotion, and 'contribute' to the focal brand's sales bump). Similarly, '*store-switching*' is the difference between baseline-sales and calendar sales, across promotion weeks and the two retailers, for the focal brand at rival stores; and '*stockpiling*' is the difference between baseline and calendar sales for the focal brand at the promoting store across periods immediately following a promotion week. Note that the figures can also be negative (for instance: a negative figure for store switching would mean that a promotion for the focal brand at a promoting chain implies higher same-week sales for the focal brand at rival chains, a negative figure for stockpiling means that the focal brand continues to sell more at the promoting chain in the week following the promotion, etc.). More details on the calculations are given in Appendix D.

Table 2.1: Brand and Retailer Descriptives

Panel A: Volume Market Shares (in %)

Category	Beer										Chips						
Retailer	**NB1**	**NB2**	**NB3**	**NB4**	**NB5**	**PL1**	**PL2**	**PL3**		**Ret.**	**NB1**	**NB2**	**NB3**	**PL1**	**PL2**	**PL3**	**Ret.**
R1	18.6	12.8	16.3	7.9	6.2	7.5	0	5.4		16.9	52.9	24.9	2.8	15.3	0	0	20.8
R2	20.2	18.3	22.3	7.0	4.2	0	6.0	0		16.1	60.9	14.0	2.6	0	18.3	0	16.9
R3	15.1	18.2	20.9	6.5	5.3	0	0	0		7.8	55.4	19.7	4.8	0	0	0	7.4
R4	20.9	13.8	20.7	9.0	4.1	0	.4	0		5.8	66.9	11.0	4.4	0	0	12.1	5.0
R5	9.0	12.6	16.8	20.1	3.9	0	0	0		4.9	63.3	8.1	6.5	0	0	0	6.0
Mean[a]	16.3	15.0	17.9	9.6	4.6	1.9	1.6	1.4			57.8	14.9	4.4	3.2	3.1	3.0	

Category	Laundry Detergents										Coffee						
Retailer	**NB1**	**NB2**	**NB3**	**NB4**	**NB5**	**PL1**	**PL2**	**PL3**	**PL4**	**Ret.**	**NB1**	**NB2**	**PL1**	**PL2**	**PL3**	**PL4**	**Ret.**
R1	27.7	20.9	7.7	8.7	2.1	15.8	0	0	0	22.8	36.9	1.8	56.4	0	0	0	21.9
R2	24.5	21.0	4.9	3.3	1.0	0	19.9	0	0	11.2	58.0	8.4	0	29.0	0	0	14.8
R3	22.6	19.0	8.8	9.7	8.4	0	0	10.6	0	6.6	56.4	6.8	0	0	30.5	0	7.5
R4	25.9	22.7	5.0	7.7	5.9	0	0	0	12.2	4.4	61.3	9.0	0	0	0	23.3	5.0
R5	18.6	24.4	6.8	2.9	6.3	0	0	0	0	4.4	64.7	6.5	0	0	0	0	4.8
Mean	22.1	20.0	6.5	6.4	5.3	4.0	6.6	2.7	4.1		54.1	6.4	11.5	5.8	6.2	4.7	

Panel B: Unit Prices (in Eurocents per volume unit)

Category	Beer									Chips					
Retailer	**NB1**	**NB2**	**NB3**	**NB4**	**NB5**	**PL1**	**PL2**	**PL3**		**NB1**	**NB2**	**NB3**	**PL1**	**PL2**	**PL3**
R1	.164 (.027)	.144 (.015)	.167 (.021)	.120 (.019)	.200 (.027)	.105 (.011)		.072 (.007)		.525 (.054)	.856 (.169)	.438 (.115)	.445 (.084)		
R2	.156 (.025)	.137 (.015)	.155 (.018)	.117 (.024)	.181 (.026)		.080 (.009)			.488 (.063)	.805 (.154)	.419 (.096)		.397 (.062)	
R3	.156 (.021)	.134 (.015)	.157 (.021)	.117 (.015)	.187 (.036)					.511 (.057)	.849 (.147)	.462 (.124)			
R4	.153 (.016)	.134 (.017)	.157 (.027)	.116 (.015)	.184 (.031)					.502 (.054)	.861 (.192)	.439 (.126)			.343 (.064)
R5	.153 (.022)	.135 (.017)	.159 (.020)	.114 (.014)	.189 (.033)					.506 (.042)	.822 (.139)	.492 (.126)			

Category	Laundry Detergents									Coffee					
Retailer	**NB1**	**NB2**	**NB3**	**NB4**	**NB5**	**PL1**	**PL2**	**PL3**	**PL4**	**NB1**	**NB2**	**PL1**	**PL2**	**PL3**	**PL4**
R1	.464 (.092)	.366 (.108)	.414 (.080)	.365 (.112)	.368 (.078)	.313 (.075)				1.034 (.127)	.499 (.073)	.760 (.085)			
R2	.449 (.093)	.341 (.098)	.332 (.108)	.313 (.056)	.315 (.077)		.186 (.026)			.908 (.127)	.477 (.062)		.696 (.128)		
R3	.469 (.105)	.352 (.099)	.440 (.091)	.339 (.063)	.354 (.088)			.299 (.071)		.943 (.126)	.527 (.088)			.758 (.165)	
R4	.468 (.096)	.332 (.088)	.417 (.088)	.339 (.059)	.363 (.090)				.288 (.061)	.950 (.162)	.548 (.129)				.755 (.177)
R5	.441 (.081)	.347 (.081)	.388 (.094)	.341 (.035)	.350 (.083)					.948 (.086)	.525 (.116)				

[a] Mean share in the total market, including 'rest' retailers

[b] Volume units : ml for beer and laundry detergents, grams for chips and coffee

Table 2.2: Feature Promotion Calendar Descriptives: Beer[a]

Panel A: Promotion Frequency by Brand and Retailer

	Frequency of promotions (weeks in promotion)						Inter-promo time (in weeks)	
	Retailer							
Brand	**R1**	**R2**	**R3**	**R4**	**R5**	**Total**	**Mean**	**SD**
NB1	60	63	65	50	17	256	5.50	8.39
NB2	29	51	44	34	14	174	8.19	7.97
NB3	42	43	38	41	18	182	8.70	12.69
NB4	31	37	45	27	15	156	8.18	6.87
NB5	34	17	44	27	16	145	11.32	15.56
PL1	4	0	0	0	0	4	7.33	7.77
PL2	0	5	0	0	0	5	77.00	85.93
PL3	12	0	0	0	0	12	21.73	30.76
Total	215	218	245	184	80	953		

Panel B: Number of Promotions per Week by National Brand and Retailer[b]

	Number of promotions per week (% of total promotions)				
Brand	**1**	**2**	**3**	**4**	**5**
NB1	153 (59.8)	39 (30.4)	7 (8.2)	1 (1.6)	0
NB2	117 (67.2)	21 (24.2)	5 (8.6)	0	0
NB3	115 (63.1)	26 (28.6)	5 (8.3)	0	0
NB4	114 (73.1)	18 (23.1)	2 (3.8)	0	0
NB5	92 (63.9)	18 (25.0)	4 (8.3)	1 (2.8)	0
PL1	4 (1)	0	0	0	0
PL2	5 (1)	0	0	0	0
PL3	12 (1)	0	0	0	0
Total	629 (66.0)	123 (25.8)	23 (7.4)	1 (.04)	1 (.05)

Retailer	**1**	**2**	**3**	**4**	**5**	**6**
R1	160 (73.4)	21 (19.3)	3 (5.5)	1 (1.8)	0	0
R2	142 (65.7)	28 (25.9)	3 (4.2)	1 (1.9)	1 (2.3)	0
R3	165 (67.3)	34 (27.8)	4 (4.9)	0	0	0
R4	130 (70.0)	17 (18.5)	4 (6.5)	2 (4.3)	0	0
R5	61 (76.2)	5 (12.5)	3 (11.3)	0	0	0
Total	667 (70.0)	106 (22.2)	17 (5.4)	3 (1.3)	1 (0.5)	1 (0)

[a] The totals include the 'rest' brand or retailer.

[b] The table should be read as follows: For brand NB1, there were 153 weeks with a promotion at one retailer, 39 weeks with a simultaneous promotion at two retailers, 7 weeks with a simultaneous promotion at three retailers, and 1 week with a promotion at 4 retailers. Hence, of the total number of retailer-promotion weeks for NB1 (256, see Panel A), 153 (or 153/256 = 59.8%) did not run concurrently with any other chain, 2*39 promotions (or 68/256=30.4%) were scheduled simultaneously at two retailers, 3*21 promotions (or: 63/256=8.2%) were scheduled simultaneously at three retailers, and 4*1 promotions (or: 4/256=1.6%) occurred simultaneously at four retailers.

Table 2.3: Variables and Operationalizations

Variable	**Operationalization**	**Model (Utility)**[a]
Promotion variables		
(Feature) Promotion	Dummy equal to one if there was a feature promotion for (more than half of the brand's SKU line) at the retailer in that week, and zero otherwise	GNL (Y^h_{brt}) + Q
Promotion at other retailer	Dummy equal to one if the same brand was on feature at another retailer in the same week, and zero otherwise	GNL (Y^h_{brt}) + Q
Lagged promotion	Dummy equal to one if the same brand was on feature at the same retailer in the previous week, and zero otherwise	GNL(Y^h_{brt}) + Q
Weeks_since_last_same	Time (log-transformed number of weeks) since previous feature promotion for the brand at the retailer, weighted by retailer household share in init. period	GNL (Y^h_{brt})+ Q
Promotion lead effect	$a1(Weeks\_since\_last\_all^h_{bt}) * \exp(-\exp(a2 * SD\_Inter\_Promo\_Time^h_{bt})$, where Weeks_since_last_all is the log-number of weeks since the last promo for that brand at any retailer (weighted by the retailer's share of household purchases in an initialization period), mean-centered by brand; SD_Inter_Promo_Time is the st. dev. of the brand's inter-promo time across chains, a1 and a2 are parameters	GNL(Y^h_{brt})
Discount depth	Difference between the brands' regular and promotion price, where promotion prices are identified as prices more than one standard deviation below the mean	GNL(Y^h_{brt}) + Q
Retailer variables		
Distance to retailer	Log-transformed distance (in km) of household to closest outlet of each retailer (updated quarterly)	GNL(Y^h_{0rt}; Y^h_{brt})
Ret. pref. (init. visit share)	Household-specific retailer share of visits in initialization period	GNL(Y^h_{0rt}; Y^h_{brt})
Last visit retailer	Dummy equal to one if household's last shopping trip occurred at the same retailer, and zero otherwise	GNL(Y^h_{0rt}; Y^h_{brt})
Last purchase retailer	Dummy equal to one if household's last purchase in the category occurred at the same retailer, and zero otherwise	GNL(Y^h_{0rt}; Y^h_{brt})
Ret. attraction other cats	The mean-centered promotion pressure for each retailer, weighted by category and retailer share (in initialization period) of each household.	GNL(Y^h_{0rt}; Y^h_{brt})
Category variables		
Purchase rate hh (init)	Household purchase incidence rate in focal category, calculated as fraction of trips with a category purchase in the initialization period	GNL(Y^h_{brt})
Lagged cat. purchase	Dummy equal to one if household's last shopping trip included a category purchase, and zero otherwise	GNL(Y^h_{brt})
Inventory	Household (mean-centered) inventory in category, updated daily, allowing for flexible consumption: $INV^h_t = INV^h_t + PURCHASE^h_{t-1} - CONSUMPTION^h_{t-1}$, where $CONSUMPTION^h_t = INV^h_t * \left[\frac{C^h}{C^h + INV_t^{h\,a3}}\right]$, with C^h= hh's average (weekly) consumption rate in the initialization period, and a3 is the consumption flexibility parameter.	GNL(Y^h_{brt}) + Q
Seasonality: Temperature	Average temperature during week	GNL(Y^h_{brt}) + Q
Seasonality: Christmas	Dummies for Christmas (last 2 weeks of December)	GNL(Y^h_{brt}) (beer)
Seasonality: Summer	Dummies for summer (July & August)	GNL(Y^h_{brt}) (beer)
Brand variables		
Last purchase brand	Dummy equal to one if same brand was purchased on household's last purchase in the category, and zero otherwise	GNL(Y^h_{brt})
Regular price	Average price per unit volume (across SKUs) for a brand in a given week, as observed in the panel data. Missing observations were replaced by 4 week moving average of the brand price at the same retailer, outliers (> 5 SD) were replaced by series mean	GNL(Y^h_{brt}) + Q
Assortment	Number of SKUs in the brand's line at the retailer (prior moving average of number of SKUs encountered in the panel, over 26 weeks	GNL(Y^h_{brt})

[a]: Model GNL: Retailer, Brand and Incidence choice, Model Q: Quantity

Table 2.4: Estimation Results

Panel A: Parameter Estimates

Model	Variable	Beer		Laundry Detergents		Coffee		Chips	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
GNL model (brand-choice, retailer-choice and incidence decision)	**Promotion variables**								
	(Feature) Promotion	.461***	.161***	1.047***	.543***	.932***	.000	.635***	.009
	Promotion at other retailer	-.068***	.046***	-.035	.002	.073***	.039	.101***	.139***
	Promo*Weeks_since_last_same	-4.102***	-	-.721		-.394		-1.719***	
	Lagged promotion	.104***	.129***	.052***	.094***	-.065***	.029*	-.158	.034***
	Weeks_since_last_all	.001	.003***	.006***	.004	-74.831	38.976	-.001***	.001
	Weeks since last_all *SD. IPtime	3.973	-	.287	-	4.563***		.210	-
	Discount depth	.734***	.197**	-.038	.180***	.134	.245**	.998***	.006
	Retailer variables[c]								
	Distance to retailer	-.572***	.221***	-.563***	.274***	-.853***	.727***	-.628***	.374***
	Ret. pref. (initial visit share)	3.533***	-	2.859***		3.361***		3.587***	
	Last visit retailer	.036***	.004	.067***	.043	-.086***	.080***	.442***	.290***
	Last purchase retailer	.389***	.074***	.291***	.047	.343***	.004	.588***	.020
	Ret. attr. other cats	.028	.032	.003	.110***	.131***	.089*	.218***	.088***
	Category variables								
	Purchase rate hh (init)	.868***	-	.891***	-	2.231***	-	1.638***	-
	Lagged cat purchase	.152***	.119***	-.216*	.344***	-.812***	.048	-.158***	.342***
	Inventory	-.871***	.294*	-.157***	.081***	-.735	.250***	-25.137***	21.885***
	Consumption flexibility	.350***	-	1.569	-	.911	-	-1.002	-
	Seasonality: Temperature	.325***	-	.028*	-	-.081*	-	.144***	-
	Seasonality: Christmas	.612***	-	-	-	-	-	-	-
	Seasonality: Summer	.033	-	-	-	-	-	-	-
	Brand variables[c]								
	Last purchase brand	.130***	.063***	.692***	.108***	.450***	.019	1.419***	.294***
	Regular price	-1.940***	1.402***	-1.260***	.671***	-.246***	.344***	-1.040***	.652***
	Assortment	.034***	.138***	.336***	.207***	.279***	.061***	.332***	.125***
	Model-Structure parameters								
	Allocation par. (transformed) η_1[b]	3.005***	.500***	2.298***	.705***	.019	.985***	.916***	.749***
	Allocation par. (transformed) η_2[b]	4.594***	.016	1.708***	2.265***	-.392	.761***	-.383***	1.201***
	Nesting par. log(γ_{R1})	-1.965***	-	-3.537***	-	-1.478*	-	.242***	-
	Nesting par. log(γ_{C1})	.027	-	-.077***	-	.069***	-	.379***	-
	Nesting par. log(γ_{B2})	-.144***	-	-.192***	-	-.033	-	-.674***	-
	Nesting par. log(γ_{C2})	-1.283***	-	-.188***	-	.516*	-	.163***	-
	Nesting par. log(γ_{R3})	.802***	-	-.420***	-	-.526***	-	-.491***	-
	Nesting par. log(γ_{C3})	.873***	-	.724***	-	1.485***	-	1.381***	-
	Loglikelihood(sig)[d]	-71462***		-28816***					
Quantity model	**Promotion-related variables**								
	(Feature) Promotion	1.125***	1.700***	.249	.267	.066***	.034***	.056***	.034***
	Promotion at other retailer	-.301***	.083	.015	.060	.007	.003	.004**	.005
	Promo*Weeks since last	.000	-	.003	-	-.001		.001	
	Lagged promotion	.132**	.131	-.074	.015	.002	.019	.007	.005
	Discount	4.648***	1.102***	.061	.075	.411***	.482***	-.030	.046***
	Controls[c]								
	Mean quantity hh (init)	0.015***		.012***		.016***		.003	
	Price	-9.317***	16.535***	-3.002***	.065	-.059	.484***	-.219***	.146***
	Inventory	1.032***	2.370***	.004	.089***	-.038**	.152***	-.383	.012
	Seasonality: Temperature	.002		.000		.000		-.001	
	Loglikelihood(error var.)	-41,087.2 (5.548)		-10,414.4 (1.322)		-25,694.0 (.522)		13,598.2(.185)	

Panel B: Estimated GNL Structure

	Beer			Laundry Detergents			Coffee			Chips		
	I→S→B	I→B→S	S→I→B	I→S→B	I→B→S	S→I→B	I→S→B	I→B→S	S→I→B	I→S→B	I→B→S	S→I→B
Allocation Pars[b]	.17	.82	.01	.60	.34	.06	.38	.25	.37	.60	.16	.24
Nesting Par. Lower level	.140	.866	2.231	.029	.826	.657	.228	.967	.591	0.510	1.273	.612
Nesting Par. Higher level	1.027	.277	2.394	.926	.829	2.062	1.071	1.675	4.416	1.1772	1.461	3.980

[a]: Estimated means and standard deviations of the household mixing distributions; *: p<0.10, **: p<0.05, ***: p<0.01.

[b]: Such that: $\tau_1=\exp(\eta_1)/(\exp(\eta_1)+\exp(\eta_2)+1)$; $\tau_2=\exp(\eta_2)/(\exp(\eta_1)+\exp(\eta_2)+1)$ and $\tau_3=1-\tau_1-\tau_2$ (see Appendix 2.A for details).

[c]: Retailer and brand constants are not reported to save space, but can be obtained from the first author.

[d]: ***: p<.01 significant improvement over MNL model, based on likelihood-ratio test.

Appendix 2.A: Estimation Issues

Identification and transformations

The GNL and Quantity models include (random) intercepts for the retailers and brands. For identification of the brand constants, the 'rest brand' (for which no separate constant is estimated) serves as the reference brand in the Quantity model, and 'no choice' is the reference in the GNL model. For the retailer constants, the 'rest retailer' is the reference in both models.

To ensure values for the allocation parameters τ_1, τ_2,and τ_3 within [0,1] and summing to 1, we estimated a transformation of these parameters, η_1 and η_2, such that: $\tau_1=\exp(\eta_1)/(\exp(\eta_1)+\exp(\eta_2)+1)$; $\tau_2=\exp(\eta_2)/(\exp(\eta_1)+\exp(\eta_2)+1)$ and $\tau_3=1-\tau_1-\tau_2$. Similarly, we estimate the log of the nesting parameters to ensure positive values.

Issues in GNL model estimation

Simulated maximum likelihood estimation of the random-effects GNL model involves maximization of the following function:

$$LL = \sum\nolimits_h ln\left[\sum_d \frac{1}{D}\left(\prod_t \prod_r ((P^h_{0r,t}|\beta^h_d)^{y^h_{0,rt}} * \prod_b (P^h_{br,t}|\beta^h_d)^{y^h_{b,rt}})\right)\right]$$

where β^h_d are household-specific draws of the parameter vector from the mixing distribution, with means and variances to be estimated, D is the number of draws for each household, $P^h_{0r,t}|\beta^h_d$ and $P^h_{br,t}|\beta^h_d$ are the probabilities in Figure 2.1 in the main text calculated at the parameter-vector draw β^h_d, and $y^h_{0,rt}$ and $y^h_{b,rt}$ are variables indicating whether a no-purchase trip (purchase of brand b) actually occurred at time t and retailer r for household h. Because the GNL model (and the corresponding likelihood expression above) contains (i) observations for all household shopping trips at all stores (irrespective of a category purchase), and (ii) choice probabilities for a large set of alternatives, i.e. (number of brands in the category + no purchase) times (number of retailers), three problems arise in the heterogeneous (random-effects) GNL specification. First, estimation time becomes prohibitive. Second, because of the large number of (potentially small) probabilities to be multiplied (i.e. the large number of trips), calculation of the likelihood for each household leads to numerical problems, which cannot be resolved with (clever) rescaling. Third, obtaining proper parameter estimates for the promotion variables (which are crucial to our analysis) is further compounded by the large number of trips without category purchases (Note that the promotion parameters only enter the utilities involving a brand purchase, see Table 2.3).

To resolve these problems, we use insights from the literature on discrete-choice model estimation with choice-based sampling. Building on this literature, instead of estimating the model on the complete data set, we first obtain a stratified sample from the households' shopping trips, in which we (i) use all the households' trips that involve a category purchase, but (ii) randomly sample from its trips without a purchase in the focal category (the 'no-incidence trips'). We do so separately for each product category, where we set the sampling rate from the no-incidence trips such that we have the same number of trips with incidence and without incidence. To illustrate, consider the beer category, for which close to 10% of household trips in the estimation sample contain a category purchase, and 90% do not. By randomly sampling one out of nine trips without a purchase, we get a balanced distribution of incidence and no-incidence trips.

Because we know the fraction Q of no-incidence trips in the 'population' (i.e. our data set including all trips, obtained from the GfK panel; e.g. for beer: Q=10%) as well as our corresponding sampling rate H (in the above example for beer: 1/9), we can then use the weighted estimation procedure described by Manski and McFadden (1981) and Cosslett (1981) to obtain unbiased estimates of our parameters. This approach maximizes the following expression, using simulated log-likelihood to obtain the maximum:

$$LL = \sum_h ln \left[\sum_d \frac{1}{D} \left(\prod_t \prod_r (\langle \frac{(P^h_{0r,t} | \beta^h_d) * \frac{H}{Q}}{\sum_r ((P^h_{0r,t} | \beta^h_d) * \frac{H}{Q} + \sum_b P^h_{br,t} | \beta^h_d * \frac{H}{1-Q})} \rangle^{y^h_{0,rt}} \right.\right.$$

$$\left.\left. * \prod_b \langle \frac{(P^h_{br,t} | \beta^h_d)}{\sum_r ((P^h_{0r,t} | \beta^h_d) * \frac{H}{Q} + \sum_b P^h_{br,t} | \beta^h_d * \frac{H}{1-Q})} \rangle^{y^h_{b,rt}}) \right) \right]$$

Though the procedure does not yield efficient estimates, this is not really an issue here, given our large number of observations. For our random effects GNL model, this speeds up estimation considerably and, more importantly, removes convergence problems from numerical underflow. We tested the procedure by comparing its outcomes with those obtained from the full sample of observations, for the homogeneous models (in which computation time is far lower as is, and numerical problems can be avoided by expressing the loglikelihood as the sum of loglikelihoods across household-trip observations). The results (both in terms of parameter estimates and their significance) were substantively the same – in support of the procedure.

Appendix 2.B: Promotion Calendar Descriptives

Table 2.B.1: Feature Promotion Calendar: Descriptives: Beer

Panel A: Promotion Frequency by Brand and Retailer

	Frequency of promotions (weeks in promotion)						**Inter-promo time (in weeks)**	
	Retailer							
Brand	**R1**	**R2**	**R3**	**R4**	**R5**	**Total[a]**	**Mean**	**SD**
NB1	60	63	65	50	17	256	5.50	8.39
NB2	29	51	44	34	14	174	8.19	7.97
NB3	42	43	38	41	18	182	8.70	12.69
NB4	31	37	45	27	15	156	8.18	6.87
NB5	34	17	44	27	16	145	11.32	15.56
PL1	4	0	0	0	0	4	7.33	7.77
PL2	0	5	0	0	0	5	77.00	85.93
PL3	12	0	0	0	0	12	21.73	30.76
Total[a]	215	218	245	184	80	953		

[a]The column totals include the 'rest' brand, the row totals include the 'rest' retailer.

Panel B: Number of Promotions per Week by National Brand and Retailer

	Number of promotions per week (% of total promotions)					
Brand	**1**	**2**		**3**	**4**	**5**
NB1[d]	153 (59.8)	39 (30.4)		7 (8.2)	1 (1.6)	0
NB2	117 (67.2)	21 (24.2)		5 (8.6)	0	0
NB3	115 (63.1)	26 (28.6)		5 (8.3)	0	0
NB4	114 (73.1)	18 (23.1)		2 (3.8)	0	0
NB5	92 (63.9)	18 (25.0)		4 (8.3)	1 (2.8)	0
PL1	4 (1)	0		0	0	0
PL2	5 (1)	0		0	0	0
PL3	12 (1)	0		0	0	0
Total[b]	629 (66)	123 (25.8)		23 (7.4)	1 (.04)	1 (.05)
Retailer	**1**	**2**	**3**	**4**	**5**	**6**
R1	160 (74.4)	21 (19.6)	3 (4.2)	1 (1.8)	0	0
R2	142 (65.7)	28 (25.9)	3 (4.2)	1 (1.9)	1 (2.3)	0
R3	165 (67.3)	34 (27.8)	4 (4.9)	0	0	0
R4	130 (70.0)	17 (18.5)	4 (6.5)	2 (4.3)	0	0
R5	61 (76.2)	5 (12.5)	3 (11.3)	0	0	0
Total[c]	667 (70.0)	106 (22.2)	17 (5.4)	3 (1.3)	1 (0.5)	1 (0)

[b] The totals include the 'rest' brand, [c] the totals include the 'rest' retailer.

[d] The table should be read as follows: For brand NB1, there were 153 weeks with a promotion at one retailer, 39 weeks with a simultaneous promotion at two retailers, 7 weeks with a simultaneous promotion at three retailers, and 1 week with a promotion at 4 retailers. Hence, of the total number of retailer-promotion weeks for NB1 (256, see Panel A), 153 (or 153/256 = 59.8%) did not run concurrently with any other chain, 2*39 promotions (or 68/256=30.4%) were scheduled simultaneously at two retailers, 3*21 promotions (or: 63/256=8.2%) were scheduled simultaneously at three retailers, and 4*1 promotions (or: 4/256=1.6%) occurred simultaneously at four retailers.

Table 2.B.2: Feature Promotion Calendar: Descriptives: Laundry Detergents

Panel A: Promotion Frequency by Brand and Retailer

	Frequency of promotions (weeks in promotion)						Inter-promo time (in weeks)	
	Retailer							
Brand	**R1**	**R2**	**R3**	**R4**	**R5**	**Total**[a]	**Mean**	**SD**
NB1	81	68	67	80	20	359	5.75	6.45
NB2	102	80	95	81	26	428	4.94	4.67
NB3	63	25	48	40	20	237	8.74	10.02
NB4	86	17	55	58	9	285	7.20	8.45
NB5	21	0	40	52	21	197	10.83	17.43
PL1	25	0	0	0	0	28	13.88	14.82
PL2	0	4	0	0	0	4	102.00	96.81
PL3	0	0	18	0	0	18	20.59	23.92
PL4	0	0	0	25	0	25	15.54	21.84
Total[a]	483	303	426	439	99	2004		

[a] The column totals include the 'rest' brand, the row totals include the 'rest' retailer.

Panel B: Number of Promotions per Week by National Brand and Retailer

	Number of promotions (% of total promotions) per week				
Brand	**1**	**2**	**3**	**4**	**5**
NB1	164 (45.7)	54 (30.1)	18 (15.0)	7 (7.8)	1 (1.4)
NB2	171 (40.0)	75 (35.0)	30 (21.0)	3 (2.8)	1 (1.2)
NB3	127 (53.5)	31 (26.2)	13 (16.5)	1 (1.7)	1 (2.1)
NB4	161 (56.5)	50 (35.1)	8 (8.4)	0	0
NB5	118 (74.3)	27 (17.6)	7 (6.8)	1 (1.3)	0
PL1	24 (85.7)	2 (14.3)	0	0	0
PL2	4 (1)	0	0	0	0
PL3	18 (1)	0	0	0	0
PL4	25 (1)	0	0	0	0
Total[b]	958 (47.8)	333 (33.3)	103 (15.4)	14 (2.8)	3 (0.7)

Retailer	**1**	**2**	**3**	**4**	**6**	**7**
R1	216 (44.7)	107 (44.3)	12 (7.5)	1 (0.8)	1 (1.2)	1 (1.5)
R2	205 (67.7)	40 (26.4)	6 (5.9)	0	0	0
R3	212 (49.8)	74 (34.7)	18 (12.7)	3 (2.8)	0	0
R4	207 (53.8)	84 (43.6)	20 (1.6)	1 (1.0)	0	0
R5	63 (63.6)	15 (30.3)	2 (6.1)	0	0	0
Total[c]	932 (46.5)	355 (35.4)	87 (13.2)	22 (4.4)	1 (0.2)	1 (0.3)

[b] The totals include the 'rest' brand.
[c] The totals include the 'rest' retailer.
[d] For interpretation of the table entries: see legend of Table 2.B.1, Panel B.

Table 2.B.3: Feature Promotion Calendar: Descriptives: Coffee

Panel A: Promotion Frequency by Brand and Retailer

	Frequency of promotions (weeks in promotion)						Inter-promo time (in weeks)	
	Retailer							
Brand	**R1**	**R2**	**R3**	**R4**	**R5**	**Total[a]**	**Mean**	**SD**
NB1	60	83	74	106	0	323	5.17	5.78
NB2	10	36	44	60	1	156	11.03	19.09
PL1	65	0	0	0	0	80	6.56	5.55
PL2	0	31	0	0	0	31	13.30	15.34
PL3	0	0	118	0	0	132	3.61	3.00
PL4	0	0	0	110	0	110	3.83	3.61
Total[a]	138	154	263	290	1	880		

[a] The column totals include the 'rest' brand, the row totals include the 'rest' retailer.

Panel B: Number of Promotions per Week by National Brand and Retailer

	Number of promotions (% of total promotions) per week			
Brand	**1**	**2**	**3**	**4**
NB1	168 (52.0)	68 (42.1)	5 (4.7)	1 (1.2)
NB2	128 (82)	11 (14.1)	2 (3.9)	0
PL1	52 (65)	14 (35)	0	0
PL2	31 (1)	0	0	0
PL3	132 (1)	0	0	0
PL4	110 (1)	0	0	0
Total[b]	655 (73.6)	100 (22.5)	7 (3.5)	1 (0.4)

Retailer	**1**	**2**	**3**	**4**	**5**
R1	126 (91.3)	6 (8.7)	0	0	0
R2	144 (93.5)	5 (6.5)	0	0	0
R3	199 (75.7)	32 (24.3)	0	0	0
R4	237 (81.7)	22 (15.2)	3 (3.1)	0	0
R5	1 (1)	0	0	0	0
Total[c]	731 (83.2)	70 (15.7)	3 (1.1)	0	0

[b] The totals include the 'rest' brand.
[c] The totals include the 'rest' retailer.
[d] For interpretation of the table entries: see legend of Table 2.B.1, Panel B.

Table 2.B.4: Feature Promotion Calendar: Descriptives: Chips

Panel A: Promotion Frequency by Brand and Retailer

	Frequency of promotions (weeks in promotion)						Inter-promo time (in weeks)	
	Retailer							
Brand	**R1**	**R2**	**R3**	**R4**	**R5**	**Total[a]**	**Mean**	**SD**
NB1	65	61	56	40	0	222	7.16	7.48
NB2	31	30	41	24	19	178	8.22	14.38
NB3	18	21	50	31	4	141	13.14	29.80
PL1	20	0	0	0	0	23	21.84	20.55
PL2	0	6	0	0	0	6	71.00	70.71
PL3	0	0	0	32	0	32	11.32	16.29
Total[a]	144	125	189	142	24	677		

[a] The column totals include the 'rest' brand, the row totals include the 'rest' retailer.

Panel B: Number of Promotions per Week by National Brand and Retailer

	Number of promotions (% of total promotions) per week			
Brand	**1**	**2**	**3**	**4**
NB1	138 (62.2)	39 (35.1)	2 (2.7)	0
NB2	71 (39.9)	29 (32.6)	11 (18.5)	4 (9.0)
NB3	94 (66.7)	22 (31.2)	1 (2.1)	0
PL1	23 (100.0)	0	0	0
PL2	6 (100.0)	0	0	0
PL3	32 (100.0)	0	0	0
Total[b]	431 (14.5)	94 (3.2)	14 (.5)	4 (.1)

Retailer	**1**	**2**	**3**	**4**	**5**
R1	130 (90.3)	7 (6.7)	0	0	0
R2	111 (88.8)	7 (11.0)	0	0	0
R3	157 (83.1)	16 (16.9)	0	0	0
R4	122 (85.9)	10 (14.1)	0	0	0
R5	24 (100.0)	0	0	0	0
Total[c]	589 (87.0)	44 (13.0)	0	0	0

[b] The totals include the 'rest' brand.

[c] The totals include the 'rest' retailer.

[d] For interpretation of the table entries: see legend of Table 2.B.1, Panel B.

Appendix 2.C: Correlation Tables

Table 2.C.1: Correlation Price and Promotion Variables

Panel A: Beer

	(Feature) Promotion	Promotion at other retailer	Promo* Weeks_ since_last_same	Lagged Promotion	Weeks since last all * SD. IPtime	Weeks_since_ last_all	Discount depth
(Feature) Promotion							
Promotion at other retailer	.062**						
Promo*Weeks_since_last_same	.004	.013					
Lagged Promotion	.214**	.105**	.002				
Weeks since last all * SD. IPtime	-.012	-.052**	-.001	-.012			
Weeks_since_last_all	-.040**	-.105**	.033**	-.093**	.155**		
Discount depth	.719**	.020*	.013	.138**	-.013	-.031**	
Regular Price	-.092**	.054**	.000	.006	-.340**	.062**	-.120**

*: p<0.05, **: p<0.01

Panel B: Chips

	(Feature) Promotion	Promotion at other retailer	Promo* Weeks_ since_last_same	Lagged Promotion	Weeks since last all * SD. IPtime	Weeks_sinc e_ last_all	Discount depth
(Feature) Promotion							
Promotion at other retailer	.094**						
Promo*Weeks_since_last_same	.024**	.010					
Lagged Promotion	.221**	.108**	.000				
Weeks since last all * SD. IPtime	-.040**	-.079**	-.001	-.040**			
Weeks_since_last_all	-.046**	-.074**	.042**	-.102**	-.110**		
Discount depth	.682**	.060**	.082**	.184**	-.024*	-.030**	
Regular Price	-.015	.147**	.010	.053**	-.099**	-.141**	-.049**

*: p<0.05, **: p<0.01

Panel C: Coffee

	(Feature) Promotion	Promotion at other retailer	Promo*Weeks_since_last_same	Lagged Promotion	Weeks since last all * SD. IPtime	Weeks_since_last_all	Discount depth
(Feature) Promotion							
Promotion at other retailer	.016						
Promo*Weeks_since_last_same	.044**	-.002					
Lagged Promotion	.208**	.002	-.001				
Weeks since last all * SD. IPtime	-.104**	-.073**	-.008	-.104**			
Weeks_since_last_all	-.043**	-.040**	.030**	-.111**	.170**		
Discount depth	.550**	-.008	.081**	.138**	-.061**	-.022*	
Regular Price	-.011	.128**	.023*	.062**	-.272**	.013	-.131**

*: p<0.05, **: p<0.01

Panel D: Laundry Detergents

	(Feature) Promotion	Promotion at other retailer	Promo*Weeks_since_last_same	Lagged Promotion	Weeks since last all * SD. IPtime	Weeks_since_last_all	Discount depth
(Feature) Promotion							
Promotion at other retailer	.167**						
Promo*Weeks_since_last_same	.030**	.017*					
Lagged Promotion	.318**	.134**	.002				
Weeks since last all * SD. IPtime	-.083**	-.043**	.002	-.082**			
Weeks_since_last_all	-.053**	-.003	.038**	-.084**	.097**		
Discount depth	.532**	.093**	.038**	.177**	-.048**	-.030**	
Regular Price	-.086**	.031**	-.007	.000	.212**	-.120**	-.147**

*: p<0.05, **: p<0.01

Appendix 2.D: Simulation Procedure

Simulation Setup

To assess the implications of the parameter estimates for the effectiveness of different promotion calendars, we use them as inputs for simulations, in which we use the actual data in a 26-week period (and promotion calendars, at all brands and retailers, in this period) as a backdrop. We then consider a number of simulation cases, in which we implement changes in the promotion calendars. In each simulation case, we consider changes in the calendar of featured price cuts for a given brand (hereafter; the focal brand), at two retailers. We consider two alternative retailer combinations: (i) scenario A: the two dominant players in the category, and (ii) scenario B: the highest-share chain with a lower share retailer. The number of feature promotions at these two retailers is set roughly equal to the actual total in the observation period, and then equally split between the retailers. Each feature lasts one week, and involves a price cut equal to the brand's observed mean discount at the two chains. Table 2.C.1 provides an overview of the simulation setup for the different categories.

To realistically assess the calendar effects (and avoid the Lucas critique), we consider simulation setups that fall within the data range. In the out-of-phase schedule, none of the focal-brand promotions concurrently occur at the two retailers. For the in-phase schedule, we let two/thirds of the promotion events coincide at the two retailers – the maximum 'simultaneity' observed in the dataset for a period of 26 consecutive weeks. The remaining promotions still take place at the two retailers in different weeks (along with any other-brand promotions, which are kept common across the two scenarios). We then compare the results across the two calendars (fully out-of-phase vs. half in-phase/half out-of-phase, or simply: out-of-phase vs. in-phase hereafter), and also confront them with the benchmark setting of no featured price cuts for the focal brand at the two promoting retailers. Specifically, using the estimated parameter estimates (means and standard deviations of the mixing distributions across households), we predict the households' probabilities of retailer choice, category purchase incidence, brand choice and quantity, (for each observed shopping trip) in each week of our planning period, under the two calendars. Households are randomly assigned parameter estimates from the mixing distribution obtained in the estimation procedure (for each household, 100 such draws are considered, the outcomes of which are then averaged to obtain the household-level results). We dynamically update all the relevant variables (e.g. state dependence retailer/brand, last time purchased, last quantity purchased, inventory, etc.), by taking draws from the outcome predictions in the previous period. Aggregating these predictions across panelists then yields the overall implications of the different calendars. Given that our parameters are estimated with uncertainty, we repeat these simulations for 100 draws from the parameter sampling distributions, to assess the significance of the calendar differences.

As indicated above, our calendar simulations run against the backdrop of other-brand promotions. Changing the calendars will also change their interplay with these other actions. To distinguish highly idiosyncratic sequencing and contemporaneous effects from systematic calendar-type effects, we verify these effects for different implementations within each calendar type, by changing the ordering of the promotions across retailers in the out-of-phase calendar, and reversing the specific week in which promotions occur in the in-phase calendar (see Table 2.C.2. for an illustration for the beer category). Moreover, across categories, we also run the simulations for larger and smaller brands (see Table 2.C.1).

Overall Calendar Differences

To assess the total impact of calendar changes for the different parties, we first aggregate the panelists' simulated purchases (i) of the focal brand and the category, (ii) at each of the two promoting retailers and across all retailers, (iii) over the entire planning horizon. We repeat this exercise by (i) aggregating the households' predicted sales values (instead of volumes), and (ii) separating out these totals between volumes sold under promotional and non-promotional conditions. Comparing these metrics for the in-phase and out-of-phase calendars, then yields insights into the overall (differences in) calendar appeal – including all possible promotion dynamics (i.e. lead and lag effects, and category expansion effects). To assess the statistical significance, for each metric: we calculate the difference between calendars for a given parameter draw, and repeat this for each of the 100 draws from the parameter sampling distributions. We then consider the percentage of draws for which the calendar differences are positive (negative).

Sales Bump Decomposition

Next, to gain further insights into the differences in mechanisms, we zoom in on the sales bump for the focal brand within the promotion weeks/chains, and trace the sources of this sales lift, for each promotion calendar, and this for each of the two promoting retailers. We note that this sales bump may not cover all promotional sales increases, e.g. if the promotion would enhance sales/consumption of non-focal brands and/or non-promoting stores, this would not show up in the sales bump. Moreover, because of the high promotion frequency, we separate out the pre-emptive switches and stockpiling effects only in the post-promotion week (Note though that the net sales and revenue effects mentioned in Figure 2.3 in the main text, *do* include dynamics across the whole planning horizon). As such, the decomposition only supplements the insights from the overall calendar-comparisons.

To obtain the decomposition, we follow a procedure similar to previous authors (see, e.g., Ailawadi et al. 2007, Foubert and Gijsbrechts 2010). First, to obtain the sales bump we compare the purchases of the focal brand at the promoting retailer during promotion weeks, with purchases in the simulated benchmark setting (without promotions for the focal brand at the promoting chains). Next, we calculate:

- the difference in other-brand category purchases at the promoting store, between the promotion setting and the benchmark setting, within the promotion weeks. If this figure is negative, this is a first source of the observed sales lift, labeled brand-switching (if it is positive, it means that the promotion actually increases other-brand sales at the promoting store).

- the difference in purchases of the focal brand at rival stores, between the promotion setting and the benchmark setting, within the promotion weeks. If this figure is negative, this is a second source of the observed sales lift, labeled store-switching.

- the difference in purchases of other brands of the category at rival stores, between the promotion setting and the benchmark setting, within the promotion weeks. If this figure is negative, this is a third source of the observed sales lift, labeled brand-store switching.

- the difference in purchases of the focal brand at the promoting store, between the promotion setting and the benchmark setting, in the week following the promotion. If this figure is negative, this is a fourth source of the observed sales lift, labeled stockpiling.

- the difference in other-brand category purchases at the promoting store, between the promotion setting and the benchmark setting, in the week following the promotion. If this figure is negative, this is a fifth source of the observed sales lift, labeled pre-emptive brand switching.

- the difference in purchases of the focal brand at rival stores, between the promotion setting and the benchmark setting, in the week following the promotion. If this figure is negative, this is a sixth source of the observed sales lift, denoted as pre-emptive store switching.

- the difference in purchases of other brands in the category at rival stores, between the promotion setting and the benchmark setting, in the week following the promotion. If this figure is negative, this is a seventh source of the observed sales lift, labeled pre-emptive brand-store switching.

It is important to note that in the main text in Figure 2.5, for ease of exposition, we (i) reverse the sign of the promotional components (such that, for instance, a 'positive' figure for 'brand switching' means that competing brand sales went down, and this component contributes to the promoted brand's sales lift), and (ii) we group the pre-emptive brand-, store-, and brand-store switching components into one 'pre-emptive switches' entry in Figure 2.5 (the full breakdown can be obtained from the first author).

Table 2.C.1. Simulation setup for different categories

	Beer	**Laundry Detergents**	**Coffee**	**Chips**
Discount Depth (%)	25			
Total # retailer-promo weeks	12			
Retailers in Simulation (share)				
Leading (R1)	16.9%	22.8%	21.9%	20.8%
Secondary (R2)	16.1%	11.2%	14.8%	16.9%
Small (R4)	5.8%	4.4%	5.0%	5.0%
Focal brand (share)	NB1 (16.3%)	NB1 (21.1%)	NB1 (54.1%)	NB1 (57.8%)

Table 2.C.2.: Alternative promotion schedules for the focal brand at the two retailers: Beer

	Predominantly *Out-of-Phase* calendars				**Predominantly *In-Phase* calendars**			
	Schedule 1		Schedule 2		Schedule 1		Schedule 2	
Week	R1	R2/R4	R1	R2/R4	R1	R2/R4	R1	R2/R4
1								
2								
3								
4								
5								
6								
7								
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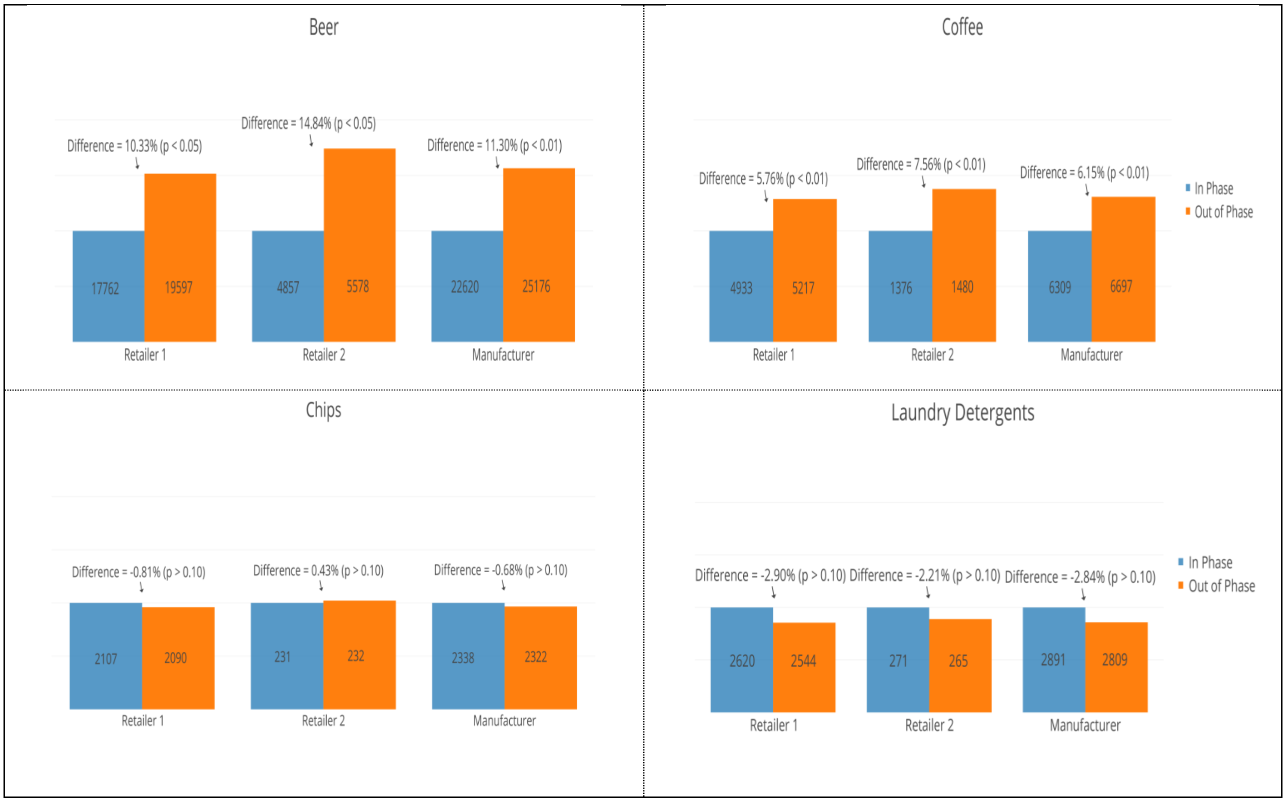
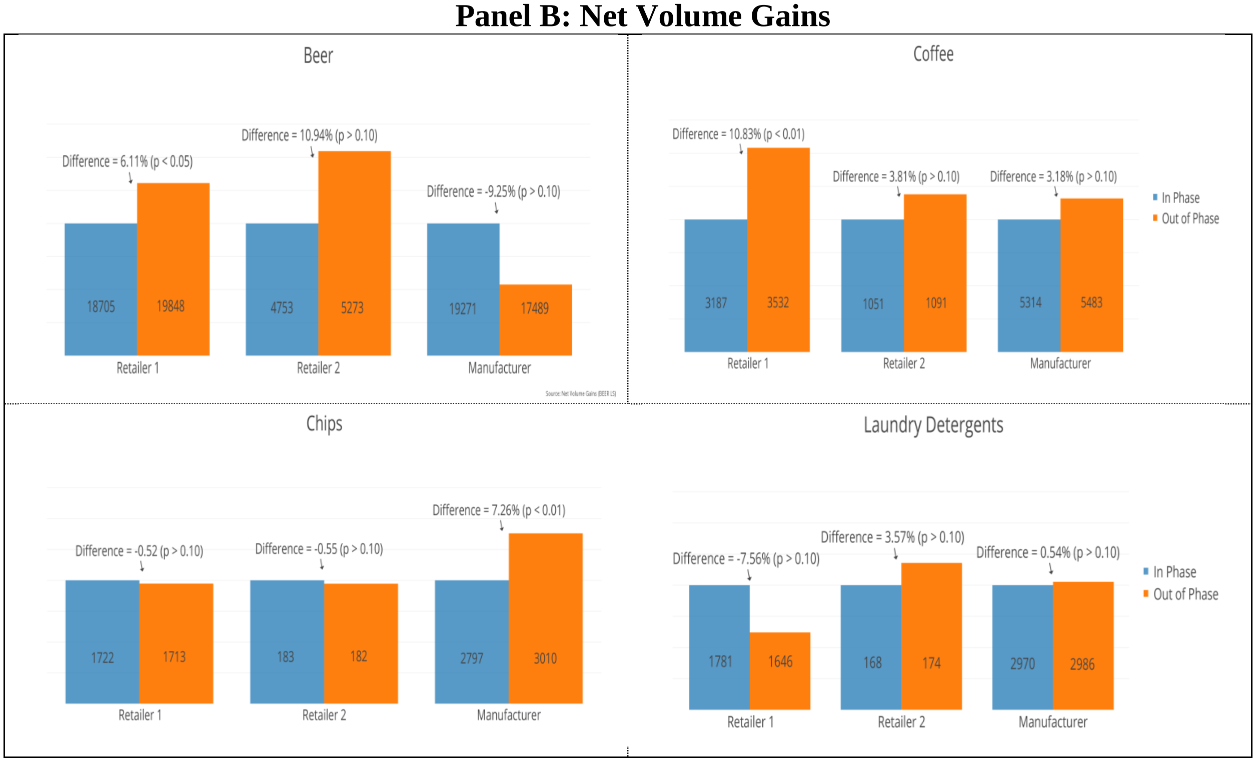
Figure C.1: Simulation Results (Leading and Smaller Retailer)

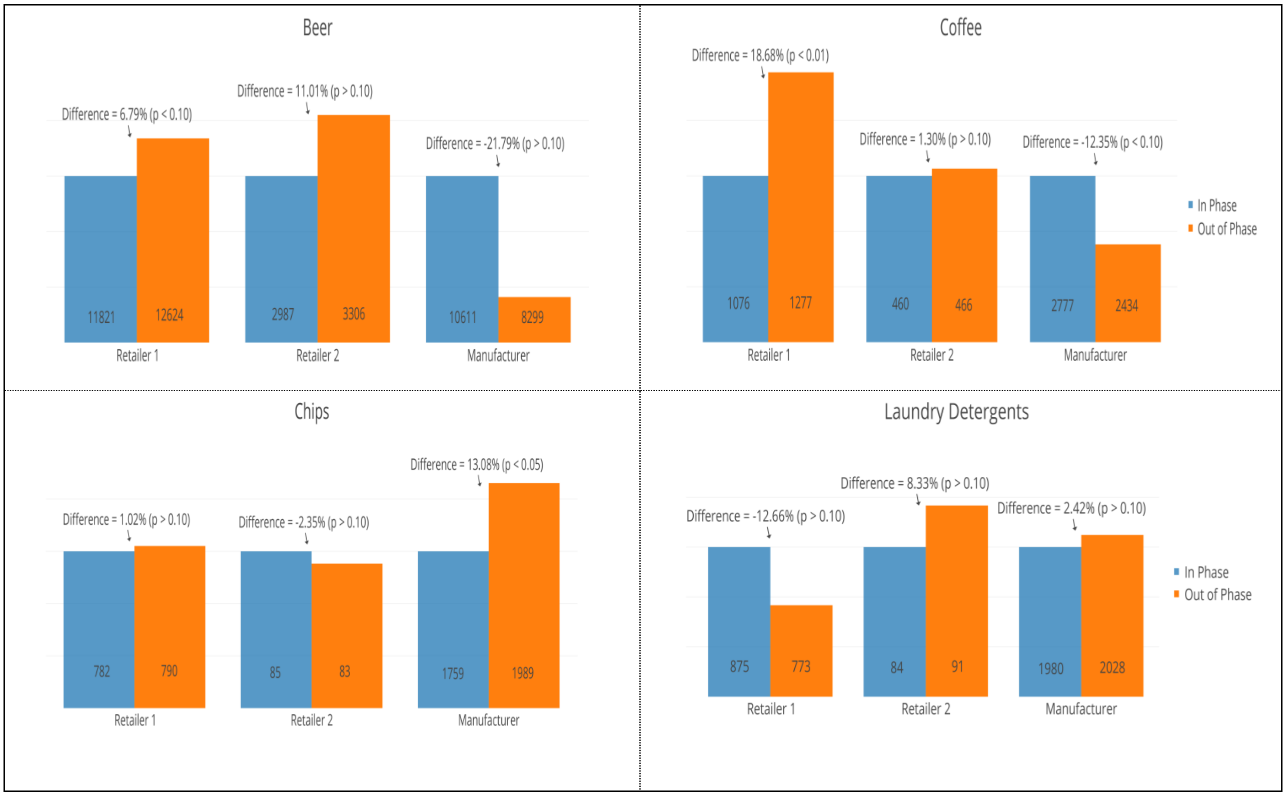
Panel A: Gross Sales Lift



Panel B: Net Volume Gains



Panel C: Net Revenue Gains



Notes: Calendar differences are calculated as Out-of-Phase minus In-Phase, divided by In-Phase. Significances based on 100 simulations. Measures are calculated over the 26 week period for the two retailers and manufacturer. For the retailer, the figures pertain to the whole category (all brands), for the manufacturer they pertain to the focal brand (at all retailers).

Chapter 3

On Consumer Decision Structures and the Impact of Feature and Discount Promotions

3.1. Introduction

Sales promotions in consumer packaged goods (CPG) markets are ever-more pervasive. Consumers' decreased willingness to pay a premium for national brands (Steenkamp et al. 2010) and their propensity to spread purchases across multiple stores (Baltas et al. 2010), have led both manufacturers and retailers to step up their promotion activities, in the form of price discounts and/or feature advertising, to attract shoppers to their brand and store (Ailawadi et al. 2009). However, whether this is money well spent, depends on how consumers choose among the available brands and stores for their CPG purchases, and on the role of different promotional actions therein.

Extant studies have typically documented the impact of promotions on brand and store sales at the market level (e.g. Srinivasan et al. 2004; van Heerde et al. 2004) or considered the effect on individual households' brand choice (e.g. Mehta and Ma 2012) or store choice (e.g. Gauri et al. 2008) separately. Little is known about how individual households trade off their category purchases across both brands and stores, and how these − possibly heterogeneous − decision patterns align with the effect of price discounts and feature promotions. Especially at times where the interplay between manufacturers and retailers has become increasingly strained, understanding how shoppers choose among brands and stores, and the role of promotions therein, is critical for the effective allocation and targeting of manufacturer and retailer sales promotion budgets.

The primary objective of this study is to shed light on the patterns of brand-retailer choice in consumer packaged goods categories, and to explore how they affect the impact of promotions on the manufacturer and retailer. To this end, we propose and estimate a generalized extreme value (GEV) model that flexibly captures shoppers' brand and store choice for a given category purchase. We estimate this model on household scanner panel data across different categories, spanning a period of 4 years. Our GEV model allows the choice of a brand-retailer combination to materialize through different decision structures, i.e. a structure in which the household primarily selects a retailer, and brands disproportionately compete with each other within that retailer ('store-focus') or, alternatively, in which the household primarily chooses a brand, and retailers disproportionally compete for that brand ('brand focus'). We expect a mixture of structures to prevail in each category, but possibly with different importance weights. Our model also allows the impact of feature ads and promotional discounts – on consumers' choices to differ between the two decision structures. Accommodating these route-dependent influences not only avoids biases in the estimated effect of promotional actions, it also leads to more refined insights into the promotional benefits for manufacturers and retailers. We use the outcomes of this model to empirically document the prevailing mixture of decision routes in multiple CPG categories. Next, we gauge the differential impact of store flyer appearances and price cuts across these decision routes for the promoted brand in the promoting store. We also consider the underlying brand switching and store switching patterns, and quantify the net consequences for the promoting brand (across stores), and for (the entire category in) the promoting store. Finally, we briefly explore the link between decision patterns and household characteristics, and reflect on managerial implications.

We contribute to extant literature in several ways. To the best of our knowledge, we are the first to (i) simultaneously consider (inter- and intra-) brand- and store-competition, taking an individual shopper perspective, and allowing for a flexible interplay between the two choice dimensions, (ii) empirically document the relative importance of these decision structures, across multiple shoppers and product categories, and (iii) explore the effectiveness of promotional price cuts and feature advertising in these decision structures. As such, our paper fits in with a 'shopper marketing' perspective (Shankar et al. 2011), in which brands' marketing activities are tailored to specific retail accounts for maximum shopper response (Kushwaha and Shankar 2013). Effective shopper marketing hinges on fine-grained insights into shoppers' purchase tradeoffs that are currently lacking (Shankar et al. 2011), and we answer a call to enhance such knowledge. Moreover, by shedding light on the choice shifts among brands and stores, we contribute to the promotion decomposition literature – indicating how the portion of the promotion lift that benefits the manufacturer or retailer is shaped by the consumers' decision structure. Uncovering how these decision routes influence the 'net' share increase from price cuts and store-flyer appearances for both parties, may provide guidance for (negotiations on) promotional targeting, feature-ad payments and discount pass-through.

Below, we briefly review relevant background literature. We then outline the methodology, followed by a description of the data and setting. Having presented the estimation results, we identify the resulting patterns of brand-store competition, and explore how they differ with shopper and category characteristics. We end with a discussion of implications, limitations, and future research areas.

3.2. Background

3.2.1. Impact of Price Discounts and Feature Promotions on Brand and Store Choice

An extensive body of literature has documented the impact of price discounts and feature ads – two of the most commonly used promotion instruments – in a wide range of CPG categories. These papers have produced generalizable findings not only on the size of the promotion bump (e.g. Ataman et al. 2008; Bijmolt et al. 2005; Bolton 1989; Hoch et al. 1995; Narasimhan et al. 1996) but also on its 'decomposition'– uncovering the sources of the sales lift of the promoted item (Ailawadi et al. 2007; Bell et al. 1999; Gupta 1988; Leeflang et al. 2008; van Heerde et al. 2003; van Heerde et al. 2004). An established finding from these papers is that promotions for CPG products may lead to both substantial brand switching *and* shifts in purchase location, where the latter mostly take the form of indirect store switching (consumers reallocating category purchases among stores they visit anyway) (see, e.g. van Heerde et al. 2004). Moreover, extant studies indicate that the (relative) size of these brand and store switching components can differ between feature promotions and discounts (e.g. Ailawadi et al. 2009; Ailawadi et al. 2006; van Heerde et al. 2004), and strongly affects the net promotion benefits for the manufacturer and the retailer (Srinivasan et al. 2004).

The majority of these studies, however, have been conducted on an aggregate level, using market- or store-wide data to document promotional changes in brand and store-category sales (e.g. Srinivasan et al. 2004; van Heerde et al. 2004). Yet, households are known to be heterogeneous in their purchase patterns and decisions: some being more committed to their favorite brand and/or likely to engage in cross-store shopping, others being more willing to switch brands yet stay with their usual store (Bucklin and Gupta 1999). Given that households' decision processes determine the competitive shifts among choice options and drive the outcome of marketing actions (Urban and Hauser 1992), the magnitude of the promotion response (i.e. whether a consumer is enticed by a deal for a certain brand and store) as well as the decomposition of the promotion bump (i.e. the portion that stems from brand and/or store switching) may well vary depending on their choice mechanisms regarding what and where to buy (e.g. Gupta 1988; Zhang 2006)). Yet, extant studies on individual households' response to promotions have either focused on brand choice (e.g. Mehta and Ma 2012), or store choice (e.g. Gauri et al. 2008), but have not considered the interplay between these two decisions – something we turn to below.

3.2.2. Decision Structures and Promotional Brand-Store Switching

CPG categories present consumers with multiple options on what to buy (i.e. which brand), and where (at which retailer). We distinguish two decision structures that lead up to the purchase of a specific brand at a specific retailer/store. In one structure, brand selection is largely conditional upon store choice – consumers picking a supermarket and, once inside the store, make their choice among the available brands inside the store (we will label this the 'retailer focus' decision route). Alternatively, consumers may primarily decide on a brand, and compare the offer of different stores carrying this brand (we will call this the 'brand focus' decision route). These different decision routes may affect consumers' promotion response and, from a managerial perspective, raise several questions. For the manufacturer: Will promoting its NB at a given store lead to share gains at the expense of other brands in the store (which is more likely in case of a store-focused decision route), or make consumers who currently decided on a brand purchase merely shift locations (as would be expected in a brand-focused decision structure)? Similarly, for the retailer: Will promoting a NB in the store primarily lead to within-store brand shifts (consistent with a retailer-focus), or also entice current non-customers to shift their category purchases toward the store (in line with a brand-focus)? And: who wins more from the promotion: the retailer or the manufacturer?

While previous studies documented promotional brand-store shifts in a category ‘in the aggregate’, we propose that consumers’ choice of brands/stores for a category purchase can be the outcome of different (brand- or retailer-focused) decision routes. We contend that within a given category, a mixture of these routes may be at work, and that each route comes with different ‘competitive shifts’ between manufacturers and retailers. We will gauge the relative importance of the alternative decision structures in a number of CPG categories, and shed light on the size of the promotion lift and its underlying brand-store shifts for each structure. In so doing, we will focus on consumers’ brand and store selection given their decision to purchase from the category at a certain point in time. Hence, from a managerial viewpoint, we will consider the manufacturer and retailer’s choice-share gains as our promotional outcome metric.

3.2.3. Decision Structures and Promotion Effectiveness

Not only will consumers’ decision structures affect the sources of promotional response (retailer-focus implying stronger within-store cannibalization, brand focus implying stronger cross-store shifts), they may also shape the relative effectiveness of different promotion instruments. As indicated by Swait et al. (2014), thinking patterns may drive attention and response to attributes of choice alternatives. Building on that insight, we expect consumers’ decision patterns to go along with different sensitivity to feature ads and temporary price discounts. For instance, consumers whose brand choices primarily materialize conditional upon store visit (the ‘retailer-focus’ decision structure), may be less influenced by store flyer ads. In contrast, consumers who primarily shop around for a particular brand (‘brand focus’), may more actively look for brand appearances in the store flyer and monitor price discounts. From the managers' viewpoint it follows that, depending on which decision structure prevails, a different mix of promotion instruments may be called for, or the impact of a given action on the manufacturer or retailer may change – issues that we explore in the empirical part.

3.2.4. Heterogeneity in Decision Structures

Consumers' brand-retailer choice processes may differ between product categories. For one, category purchase frequency may play a role: for frequently needed categories, consumers are less likely to shop around for a particular brand, but rather engage in a category purchase (pick a product from the shelf) whenever they shop at a given store (Gijsbrechts et al. 2008; Krider and Weinberg 2000). Also, consumers are more likely to adopt a within-retailer focus for categories that are less 'consequential' and do not warrant a separate store visit (Briesch et al. 2013), or for categories that are less planned/more impulsively bought - often more hedonic food items (Inman et al. 2009). So, depending on the considered category, the 'what' and 'where' decisions may be more or less prevalent.

Within a category, the predominant brand-retailer decision structure may differ among households. For instance, time constraints, overall shopping needs and income constraints have been shown to affect consumers' inclination towards one-stop shopping or, alternatively, willingness to shop around (Baltas et al. 2010). Also, households may differ in their category needs (e.g. Haans and Gijsbrechts 2011), planning of grocery purchases (e.g. Inman et al. 2009) and brand commitment (e.g. Steenkamp et al. 2010); and this, too, will affect how they shop for category products (Inman et al. 2009). As such, we need to accommodate heterogeneous decision routes within each category.

In the remainder of this paper, we empirically examine the decision patterns and their associated importance of utility drivers. Next, we compare the implications of feature ads and temporary discounts for the promoted brand-store alternative, as well as the brand and retailer as a whole; under different decision structures. In the next section, we first present the model that allows us to assess the consumers' decision routes.

3.3. Methodology

Consider a specific category (*c*; to save space we will omit the category subscript), and let *h* be a household indicator, and *t* an indicator for a category purchase occasion (trip). We use *b* and *j* as indices for brands in the category, and *r* and *s* to denote stores in which the category can be bought. On each purchase occasion, *t*, the household selects a brand-retailer combination from the available brands and stores that maximizes its utility. The utility of buying brand *b* from retailer *r* on occasion *t* for consumer *h*, conditional upon category incidence is given by:

$$U_{br,t}^{h} = V_{br,t}^{h} + \varepsilon_{br,t}^{h} = \beta^{h} X_{br,t}^{h} + \varepsilon_{br,t}^{h} \qquad (3.1)$$

where $V_{br,t}^{h}$ is the systematic utility component, specified as a function of drivers $X_{br,t}^{h}$, and $\varepsilon_{br,t}^{h}$ is the random component.

To address our research questions, we need a flexible model that allows for (i) different decision routes/structures, and (ii) differences in effectiveness of marketing instruments depending on these decision routes. The generalized extreme-value (GEV) model that we propose meets these criteria.

First, it incorporates two distinct decision patterns, each of which follows a nested logit-type structure, but where alternatives are grouped ('nested') either along the 'retailer dimension' (the retailer-nesting structure, which corresponds to our retailer-focused decisions) or along the 'brand dimension' (the brand-nesting structure, which captures the brand-focused decision route). As such, the model is more general than the (commonly used) nested logit specification, which allows the grouping of alternatives along one dimension only. In our model, the choice probability for an alternative (i.e., a specific retailer-brand combination) is obtained as the sum of two sub-probabilities - one for each nesting structure:

$$P_{br.t}^{h} = P_{br.t|d_{ret}}^{h} + P_{br.t|d_{brand}}^{h} \tag{3.2}$$

where the probability for an alternative in the retailer-nesting structure is given by:

$$P_{br.t|d_{ret}}^{h} = \frac{(\tau_1 \exp(V_{br,t,d_{ret}}^{h}))^{1/\gamma_{ret}}}{\sum_s (\tau_1 \exp(V_{bs,t,d_{ret}}^{h}))^{1/\gamma_{ret}}} * \frac{(\sum_s (\tau_1 \exp(V_{bs,t,d_{ret}}^{h}))^{1/\gamma_{ret}})^{\gamma_{ret}}}{D1 + D2} \tag{3.3}$$

and the probability in the brand-nesting structure by:

$$P_{br.t|d_{brand}}^{h} = \frac{(\tau_2 \exp(V_{br,t,d_{brand}}^{h}))^{1/\gamma_{brand}}}{\sum_j \tau_2 (\exp\left(V_{jr,t,d_{brand}}^{h}\right))^{1/\gamma_{brand}}} * \frac{(\sum_j (\tau_2 \exp(V_{jr,t,d_{brand}}^{h}))^{1/\gamma_{brand}})^{\gamma_{brand}}}{D1 + D2} \tag{3.4}$$

with D1 equal to

$$\sum_j (\sum_s (\tau_1 \exp(V_{js,t,d_{ret}}^{h}))^{1/\gamma_{ret}})^{\gamma_{ret}} \tag{3.5}$$

and D2 given by

$$\sum_s (\sum_j (\tau_2 \exp(V_{js,t,d_{brand}}^{h}))^{1/\gamma_{brand}})^{\gamma_{brand}} \tag{3.6}$$

Note that for private labels, which are the sole member of their respective brand group, expression (3.3) collapses to

$$P_{PL.t|d_{brand}}^{h} = \frac{\left((\tau_2 \exp(V_{br,t,d_{brand}}^{h}))^{1/\gamma_{brand}}\right)^{\gamma_{brand}}}{D1 + D2} \tag{3.7}$$

The GEV model thus allows products to compete differently with a set of (pre-defined) other products. The two nesting structures differ in the *nature* of the disproportionality, i.e. *whether* disproportional substitution occurs among alternatives of the same retailer (retailer nesting structure) or of the same brand (brand nesting structure). The nesting parameters then further reflect the *degree of disproportionality within each structure*: In the retailer nesting structure, the 'nesting parameter' γ_{ret} governs the intensity of competition within retailers, in the brand-nesting structure, γ_{brand} governs the degree of competition within the national-brand nests. In all, this implies that the substitution patterns can differ between (i) same-brand alternatives, (ii) same-retailer alternatives and (iii) alternatives that involve a different brand and retailer. A nesting parameter closer to (0) 1 indicates a (stronger) weaker within-group competition/substitution effect. In Equation (3.3), the allocation parameters τ_1 and τ_2 add up to 1. We expand on their interpretation below. If γ_{ret} equals 1, equation (3.3) reduces to an MNL type choice pattern (and the model becomes a mixture of a multinomial logit structure and a nested logit structure with alternatives nested by brand). If γ_{brand} equals 1, equation (3.4) becomes an MNL structure (and the model is a mixture of MNL and retailer-nested-logit structures). The model can collapse to simple MNL-model if both γ_{ret} and γ_{brand} equal 1.

Second, in Equations (3.3)-(3.7), the systematic utility of a given brand-retailer combination may differ between the two decision structures (as indicated by the subscript d_{brand} or $d_{retailer}$). Indeed, to account for possible differences in the effectiveness of marketing tools depending on the decision structure, we closely follow Swait et al. (2014) and allow households to have different 'taste parameters' in the brand-nesting and retailer-nesting structure (i.e.: we make β^h specific to the decision pattern: $\beta^h_{d_{ret}}$ and $\beta^h_{d_{brand}}$). Specifically, this also implies that our feature and discount effects differ between the patterns. A consequence of this flexibility is that the allocation parameters (τ_1 and τ_2) are not directly interpretable as the relative importance of each decision structure, given that the utility scales (and their nesting totals D1 and D2, in Equations (3.5)-(3.6)) need not be equal in both sub-structures. Rather, we will conceive the ‘probability contributions’ given by the two terms in Equation (3.2) - in which τ_1 and τ_2 obviously play a role - as indicative of the relative importance of the two decision structures.

3.3.1. Utility Drivers

As drivers of brand-retailer choice we include promotional variables and a set of controls. To capture the effect of feature promotions we include a dummy variable (*Feature*), that indicates whether a brand-retailer combination is featured in a store flyer in a given week. The discount variable (*Discount*) captures the relative depth of the discount for all prices more than one S.D. below the regular price (we follow the approach used in Geyskens et al. 2010). Our controls include a set of brand dummies (to capture differences in ‘base’ preference between brands) and retailer dummies (which account for differences in ‘base’ appeal of the store for the considered category)[16]. To capture carry-over effects, we add two dummies that indicate whether the household’s last category purchase pertained to the same retailer and/or brand (*State Dependence Retailer, State Dependence Brand)*. We include a regular price variable (*Price*) alongside an assortment variable (*Assortment*), capturing the effect of non-promotional price and assortment variation in the category on product choice. Moreover, because category purchases do not occur in isolation, we include a household-specific store-attractiveness variable measuring the store’s appeal in the remaining categories (*Retailer Attraction)* for a given household. This variable is calculated using the promotional pressure (the mean-centered percentage of products sold on promotion) in each remaining category in the store, weighted by the category’s spending share in the household’s overall shopping basket. We also incorporate a household-specific retailer visit-share variable (*Retailer Share*) to account for different levels of overall store patronage (irrespective of the category bought) among households, next to household distance to

[16] Note that, because we estimate the model by category, the store intercepts are category-specific and reflect the appeal of the store for that category.

the retailer (*Distance).* These controls account for the fact that (i) store choice is not driven by one brand/category alone but also depends on store-wide characteristics and temporary offers in other categories, and (ii) households differ in their access to stores and tendency to (re)visit a given store. Table 3.1 gives an overview of the variables and the operationalization.

--- Insert Table 3.1 about here ---

3.3.2. Estimation

To accommodate unobserved heterogeneity across households, we use normal mixing distributions for the parameter vectors, the means and standard deviations of which are decision-structure specific, as are the idiosyncratic household-shocks: $\beta_d^h = \bar{\beta}_d + \sigma_{\beta,d} * \varepsilon_d^h$, where ε_d^h is a decision-structure-specific vector of (i.i.d) standard-normally distributed errors. We estimate the model using simulated maximum likelihood. To ensure positive values of the nesting parameters, we estimate the log-transform of these parameters. Similarly, to ensure values of the allocation parameters (that will feed into the decision structures' probability contributions) between zero and one and summing to one, we re-write them as $\tau_1 = \exp(\rho)/(1 + \exp(\rho))$ and $\tau_2 = 1 - \tau_1$, and estimate the parameter ρ (see, e.g. Zhang and Breugelmans 2012 for a similar approach).

3.4. Data and Setting

3.4.1. Setting

To examine consumers' brand-retailer choice patterns for grocery items, we use panel data comprising household purchases in the CPG-industry in the Netherlands, spanning a period of 4 years (2007-2011). We study these households' purchases in 9 different categories, listed in Table 3.2. Using Dhar et al. (2001)'s terminology, these include staples (i.e. high penetration, high frequency categories: frozen pizza, chips, coffee, beer) and variety enhancers (high penetration, low frequency items: mayonnaise, ketchup and kitchen tissue), next to: niche (low penetration, high frequency: beer) and fill in categories (low penetration, low frequency: muesli and liquid detergents)[17], and hence constitute a varied set to explore consumers' decision structures. For each shopping trip on which a category purchase is made, we consider which brand was chosen, and where the purchase took place. We include the top 7 retail chains, which jointly cover 60% of the Dutch grocery market, and group the remaining retailers into a 'rest' retailer. For each category, we consider the top brands that, together, make up 80% of the (cross-retailer) sales within the category. Additionally, if a brand contributes to more than 10% of the sales within a specific retailer, we also consider it, leading to the inclusion of standard private labels in our setting.[18] Lastly, we only consider a brand to be available within a retailer if its sales within the retailer exceed 1% of the total retailer sales. We group the remaining brands into a 'rest' brand. Finally, for each category, we estimate the model on a randomly drawn subsample of 300 households that buy from the category, and remain in the panel for at least 2 years.

3.4.2. Descriptives

Table 3.2 presents some basic category descriptives. The number of brands considered in each category ranges from a minimum of 7 (frozen pizza) to a maximum of 16 (kitchen tissue). The purchase frequency differs highly between categories, with chips being the most, and liquid detergents the least often-bought categories. Each household typically buys more than one brand per category in the considered period, especially for the more frequently purchased items. Moreover, in each category under study, households not only buy different brands, they also patronize different retailers. For example, for mayonnaise, households on average purchase about

[17] Category purchase frequency and penetration was based on the GfK purchase data. A priori, we excluded categories that did not contain branded items (e.g. fresh products) or were not part of the stores' regular assortment. We also excluded categories with too many (or too few) brands – for which covering 80% of purchases would result in too many (few) choice alternatives – as well as categories with very low penetration or purchase frequency (for which our available scanner panel data would be too sparse).
[18] Some chains also offered economy private labels and premium private labels, but these were too small to be part of the 'top brands' list, and thus taken up in the 'rest brand'.

three different brands, bought at more than two different retailers.[19] This further underlines the need to take multiple retailers into account when analyzing household response to promotions. The category share of retailer sales varies between 1.82% (beer) and .1% (ketchup) – figures that, for a given category, are roughly similar across retailers.

--- Insert Tables 3.2 and 3.3 about here ---

Zooming in on brand-level characteristics, we also see a fair amount of variation within and across categories on key metrics. Table 3.3, Panel A displays the mean price and market share of the top 3 national brands (selected based on market share across all retailers) within the top 3 retailers (selected based on sales for the respective NBs) over our observation period. While some categories have one or two very strong national brands (e.g. ketchup, liquid detergents, mayonnaise), others are less concentrated (e.g. beer). Prices differ both across retailers and across brands, providing consumers with a differentiated supply of alternatives. Table 3.3, Panel B shows the promotional activity of brands and retailers, showcasing that there is ample opportunity and incentive for households to engage in promiscuous shopping behavior. In select categories (e.g. beer), brands are on feature within a single retailer roughly one out of every five weeks (e.g. NB1 is on feature in 21% of the weeks) and retailers advertise at least one product in their flyer every week (e.g. for Retailer 3 there is a likelihood of 1.29 that any NB has a promotion), whereas in other categories (e.g. mayonnaise), retailers tend to only have a product on feature once every 10 weeks (e.g. the likelihood of any NB being on promotion at retailer one in a given week is 0.11) and specific brands are promoted even less frequently. The average discounts that retailers offer tend to be largely similar within categories.

[19] These figures pertain to the (estimation) period of observation for the considered households, which is 3.5 years for most households, but somewhat shorter (with a minimum of 2 years) for households that were not in the panel throughout.

On the whole, these descriptives show that households do patronize a variety of stores and opt for different brands, and that both feature ads and temporary price cuts are frequently used by manufacturers and retailers to influence this selection process. The question remains: how do these choices come about, and what are the shifts produced by the promotion actions under different decision routes? Our GEV model sheds light on this issue.

3.5. Results

3.5.1. Model Fit

For each category, we estimate a series of 4 different models (three benchmark models, and the ‘full’ GEV model). As benchmark models, we consider (i) an MNL model, (ii) a nested logit (NL) model with alternatives nested within a retailer and (iii) a NL model with alternatives nested within a brand. We note that our full GEV model is a generalized version of the benchmark models and under certain conditions is equivalent to the benchmark models. Table 3.4 provides an overview of the models, along with some key fit statistics. The results show that in all categories under consideration, the GEV specification, which allows for a mixture of two different decision structures (retailer-nesting and brand-nesting) outperforms the MNL or NL models that accommodate only a single structure – with lower AIC and BIC values. Below, we therefore focus on the parameters of the full model. We note upfront that, for our promotion decomposition along decision structures to have practical relevance, two conditions have to be met. First, the subgroups have to be sufficiently sizable, i.e. each decision structure must explain a non-negligible portion of consumer choices in a category. Second, the decision structures must lead to distinct promotion effects, in terms of size and/or sources of the promotion lift for the considered instruments (feature ads and price cuts). We consider both aspects subsequently.

--- Insert Table 3.4 about here ---

3.5.2. Estimation Results

Table 3.5 summarizes the estimates of the GEV model for each category. To save space, we omit the brand- and retailer-constants, and report only the population-mean estimates for the heterogeneous parameters (an example of the full set of estimation results can be found in Appendix 3.A). Some interesting findings emerge.

--- Insert Tables 3.5, 3.6 and 3.7 about here ---

Decision structures. As the bottom row of Table 3.5 shows, the transformed parameters ρ do not take on very high or low values (i.e. they range between -3.6 and 2.5), leading to allocation parameters for the brand and retailer structures that differ from both zero and one. Hence, as was already clear from the fit statistics, in each category a mixture of structures is present. This is further documented in Table 3.6, which provides the relative importance – measured as the (average) contribution to the overall probability, see Equation (3.2) – of each decision structure. As can be seen from the table, each decision structure contributes at least 30% to the category total. The retailer focus is slightly more predominant for the niche (beer) and staple (chips, coffee and frozen pizza) categories, with probability contributions between 51 and 59%), while the less-frequently bought (fill in or variety enhancing) items show a somewhat higher brand focus (up to 70% for ketchup).

Recall that the different decision structures reflect whether consumers disproportionally switch between alternatives within the same store (retailer focus) or within the same brand (brand focus). The estimated nesting parameters shed further light on the strength of the disproportionality, i.e. on the ‘degree’ of within store or brand switching for each of the two decision structures. On the whole, the nesting parameters in the retailer-focused route tend to be low (and lower than their brand-focus counterparts), pointing to strong within-store cannibalization. In contrast, households in the brand-focus route have higher nesting-parameter values (for ketchup and liquid detergents, not significantly different from 1).[20] So, even in categories where the brand-focus is more common, consumers still have a non-negligible propensity to switch brands. Overall, we find that choices in a category come about as a result of heterogeneous decision structures across households; with some differences in the nature and relative importance of these structures between categories. Thus, the different subgroups (households adopting one or the other decision structure) are sufficiently sizable to warrant further investigation – the question remaining: do they also lead to distinct promotion effects? The model parameters shed some first light on this point.

Utility-driver estimates. Zooming in on the control variables first, we find that the estimates of the utility drivers in Table 3.5 show face validity, with parameter estimates that are mostly significant with the expected sign,[21] in each category and overall. In both decision structures (Panel A: retailer focus, Panel B: brand focus), we find positive and significant effects of assortment, retailer share of household visits, and retailer attraction (i.e. overall store promotion activities in other categories). Also, the coefficients of retailer and brand state dependence are positively significant in both decision structures, indicating that households have some tendency to repurchase a same brand/revisit a same store over time, irrespective of whether

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[20] Our estimates pertain to the log of the nesting parameter. To assess whether the nesting parameter itself significantly differs from one – one implying proportional substitution – we used Monte Carlo simulation, which provides an easy way to get the empirical distribution of a non-linearly transformed variable and assess significance. We (i) took 1000 random draws from the (normal) distribution of the (log-transformed) estimate, (ii) computed the exponential function of each draw, and (iii) assessed what fraction of this empirical distribution was above (or below) one.

[21] The magnitude of the parameters, which depends on the measurement scale of the corresponding utility driver, is not indicative of the effect size as such, but must be converted into scale-free elasticities or marginal effects. Because the analytical elasticity (marginal effect-) expressions for our GEV model are quite involved, we do not separately calculate them for the non-focal (control) variables. For our focal (promotion) variables, the effect sizes will be documented through the simulations (which form the counterpart of such elasticities and, as advocated by van Heerde et al. 2003, also provide insights into the absolute promotion effects).

their primary focus is on retailer or brand choice. Price of the brand at the retailer, and retailer distance, have the expected negative impact.

Next, we zoom in on the promotion variables. Considering the *significance* of the estimated parameters (Table 3.5) in each decision structure, an interesting pattern of effects emerges. Price discounts hardly play a role in the retailer-focused structure (Panel A): they exert a significant positive effect in only one category (frozen pizza), and the overall impact (across categories, based on a meta-analytic test)[22] is insignificant (z=1.15, $p>.10$).[23] The picture is somewhat different in the brand-focused decision structure (Panel B), where deeper discounts lift the purchase probability in several categories, and their impact is significant overall (z=5.64, $p<.01$). Hence, offering deeper price cuts does not pay off among households with a retailer focus, while it does increase the promoted alternative's appeal among households primarily focused on the brand. Feature ads, in turn, exert a significant effect in virtually all settings. In the retailer-focused decision structure (Panel A), their effect is significant in most categories (7 out of 9), and overall (z=31.65, $p<.01$). Their influence appears even more systematic in the brand-focused structure, with significant effects in each category, and overall (z=35.14, $p<.01$).

Having established (the lack of) significance, interesting for our purposes is a comparison of the promotional effect *sizes* across decision structures in a given category. However, the parameter estimates are not comparable as such, because of possible differences in the 'scale factor' between the structures. Moreover, the coefficient estimates do not tell the whole story. The impact of feature and discount activities will interact with other utility drivers (i.e. state dependence, and intrinsic brand and store appeal as reflected in the brand and store constants).

[22] Combined significance across categories is determined using a meta-analytic test of adding weighted Z's (with weights equal to the sample size of the categories; Rosenthal 1991).
[23] In some categories, we even find a significant negative influence, indicating that discounts make the alternative less likely to be purchased within the retailer-focused decision structure (but not necessarily overall).

Moreover, the question remains how changes in the choice probability of a promoted brand-store alternative, will affect choices for the brand (manufacturer) or category at the store (retailer) as a whole. We explore these effects in the next section.

3.5.3. Impact of Feature and Discount Promotions

Having established the prevalence of different decision structures, the question remains whether they lead to distinct promotion effects. Do the decision routes influence the size of the promotion bump? Do they affect the sources of the choice-share increase for the promoted alternative (i.e. within-brand or within-store cannibalization), and thus the net manufacturer or retailer gains? Last, but not least, do they shape the relative effectiveness of feature ads and price discounts? To answer these questions, we simulate the impact of feature ads and promotional price cuts, using the estimates from the full GEV model. First, for each household-trip and choice alternative (national brand - traditional retailer combination) in the dataset, we predict the 'benchmark' choice probability absent any promotional activity, as well as the portion of this probability stemming from the first and second decision route in the category. Next, for each choice alternative in turn, we introduce a feature ad, and calculate the new set of choice probabilities, as well as the split between decision structures (for the featured alternative and all other alternatives). We do the same for a 25% promotional price cut. Finally, we compare the choice probability contributions of each decision route, for the promotional conditions and the benchmark condition.

--- Insert Table 3.7 about here ---

Feature and discount impact on the promoted alternative. Table 3.7 summarizes how feature ads (Panel A) and price discounts (Panel B) differently change the probability of the promoted alternative (average across all NB alternatives at traditional supermarkets), by reporting the probability shifts in each decision structure, along with the significance of the underlying discount or feature estimate. The table confirms that, in general, feature promotions are the more effective tool to increase the promoted alternative's performance. They lead to increases in choice propensity between 1.1 and 2.1 percentage points (see last column of Table 3.7, panel A), which, on average, comes down to a 'doubling' of the alternative's choice propensity absent the flyer promotion. At the same time, these figures strongly differ within categories depending on the decision structure. On the whole, feature effects are much stronger in the brand-focused decision structure. This particularly holds true for the less-frequently purchased food categories (ketchup, mayonnaise, muesli) and non-food categories (kitchen towel and liquid detergents), where the feature effect tends to more than triple among brand-focused (compared to retailer-focused) households. Turning to the discount effects (Table 3.7, Panel B), we find that while the impact on the discounted alternatives' overall choice propensity is small (on average: .15 percentage points, see last column of Table 3.7, panel A), with the exception of ketchup, we find no positive effect of discounts in the retailer-focused decision structure, and any significant positive effect stems from brand-focused households. In sum, the results underscore that (i) the impact of both promotion instruments differs between the two decision structures, (ii) features lift the choice propensity of the promoted alternative among all consumers, but typically more strongly so among brand-focused households, and (iii) discounts appear to only exert an impact on brand-focused households. These results, however, pertain to the specific brand-store alternative – the question remaining what happens for the brand or store (category) as a whole. This question is particularly relevant in light of the fact that the two decision structures imply different patterns of within-store and within-brand cannibalization. As such, the effects may play out differently for the manufacturer or the retailer as a whole – something we explore next.

Brand-level and retailer-category level impact of NB promotions. Table 3.8 displays the impact of feature ads (Panel A) and price discounts (Panel B) for a NB, on the choice probability of (i) the promoted brand-retailer alternative (see column: 'Focal Brand_Retailer Alternative'), (ii) the promoting brand as a whole (i.e. at the promoting store plus other retailers, see column 'Focal Brand'), and (iii) the promoting retailer (including all alternatives within the category at that retailer, see column 'Focal Retailer'), and this for the two decision structures (retailer focus or brand focus). As such, next to the lift for the promoted alternative, it reflects the 'net brand gains' from the promotion (after accounting for within-brand cannibalization, i.e. reduced own-brand sales at rival stores), and the 'net retailer gains' (after accounting for within-store cannibalization, i.e. drops in choice propensity of other category-alternatives within the store). Moreover, for each category and decision structure, it reports the difference in net gains between the manufacturer and the retailer, as a fraction of the lift for the promoted alternative (see column '(Focal Brand - Focal Retailer)/(Focal Brand_Retailer Alternative)' in Table 3.8). Several points are worth noting.

First, the table underscores that, for a given category, the portion of the probability gain of the promoted alternative that accrues to the manufacturer or the retailer, strongly differs between decision structures. Indeed, zooming in on the cases where significant promotion lifts occur, we find that overall, the manufacturer retains a much larger 'net' portion of this lift than the retailer in the retailer-focused compared to the brand-focused decision structure (i.e the entries in the column '(Brand-Retailer)/Alternative' are larger in case of a retailer-focus compared to a brand-focus). A striking example is muesli, where in the retailer-focused decision structure, the brand hardly suffers any cannibalization but the retailer enjoys no net gains, whereas in the brand-focused structure both parties enjoy similar gains. This confirms that, for a given player (manufacturer or retailer), the *source* of his sales gain from a given promotion in a given category, will be shaped by consumers' decision routes. The implications in terms of absolute gains are not clear upfront, though. For instance, even with disproportional within-brand switching, the manufacturer may still enjoy higher absolute share increases than the retailer.[24]

Second, this thus leads to the question: for a given party, which structure yields the largest net promotional effect? The results in Table 3.7 already revealed that the lift for the promoted alternative is typically larger among brand-focused households (with some exceptions, like coffee). Since such decision structure also comes with lower cannibalization for the retailer, it follows that his net gains will also be higher under that choice structure. So, on the whole, retailers enjoy larger net gains from promotions among brand-focused than retailer-focused households. For the manufacturer, this is not clear cut a priori: even if brand-focused decision structures come with larger lift for the promoted alternative, this may be offset by enhanced within-brand cannibalization. Interestingly, Table 3.8 shows that this is not the case. Comparing the net brand gains across the two decision structures we find that, in the majority of cases, the manufacturer still reaps more from brand-focused households. For instance, zooming in on the feature effects (Table 3.8, panel A - the picture is less clear for discounts across categories, a result mostly driven by the often insignificant effects), we observe that in all categories where a brand-focus lead to higher lift for the promoted alternative (7 out of 9 categories), such decision structure continues to also entail higher *net* brand gains. In all, this suggests that despite the difference in underlying switching patterns, when it comes to promotions the interests of

[24] We note that the 'proportional switching' benchmark applies at the level of the specific brand-retailer choice alternatives. Because brands and retailers differ in the number and appeal of the choice alternatives that they offer, even among consumers with a brand focus, the manufacturer may still gain more in net terms (across his entire offer) than the retailer; and even among consumers with a retailer focus , the retailer may still gain more in net terms (across his entire offer) than the manufacturer.

manufacturers and retailers seem to be aligned – both parties getting higher promotional (net) gains from brand-focused households.

Third, the question then remains: who benefits more *within a given decision structure*, is it the manufacturer or the retailer? Again, Table 3.8 provides some insights here. Comparison of the net gains for the brand and retailer within the retailer-focused decision structure, reveals that in the vast majority of cases (where a significant effect of the promoted alternative was found to begin with), the manufacturer gains exceed the retailer gains. For instance, zooming in on the feature effects (Panel A), we find this to be true for 8 out of 9 categories. In the brand-focused decision structure, the pattern becomes more mixed, with brand gains still exceeding retailer gains in 5 out of 9 categories, but the retailer gaining more in 3 categories.

3.6. Discussion

Feature promotions and discounts have become widely used tools to influence purchasing behavior in the retailing industry. Existing literature has extensively documented differences in effectiveness of these tools (e.g. van Heerde et al. 2004) and suggested different (and perhaps overlapping) roles for these types of promotions (e.g. Zhang 2006). We extend the previous literature by providing new insights into the roles of feature promotions and discounts in decision structure that consumers use.

3.6.1. Main Findings

First, we show that all categories are characterized by substantial differences in households' decision routes, with some cross-category variation in the prevalence and nature of these routes. Frequently-purchased food items, including staples (frozen pizza, chips and coffee) and niche items (beer) exhibit a balanced mixture: in about half of the cases, households primarily choose a retailer, and brands within the retailer more strongly compete; in the other half, households primarily pick the brand, and there is clear cannibalization within the brand. In less-frequently purchased variety-enhancing (mayonnaise, ketchup, kitchen tissue) and fill-in categories (liquid detergents, muesli), consumers are somewhat more brand than retailer focused, but among those who primarily select a brand (store), the degree of within-brand (within-store) cannibalization is less (more) pronounced. Hence, within each category, observed choice patterns are quite heterogeneous in nature.

Second, these shopper decision processes influence the impact of different promotion instruments. Overall, we find the feature ad effect to be significant in either decision structure, but – especially for less-frequently purchased items – stronger among brand-focused households. Price cuts, by and large, do not exert a significant effect in case of a retailer focus, but do play a role in the brand-focused decision structure. Hence, promotions appear more effective among households for whom brand choice has prevalence over store choice.

Third, decision routes not only lead to different effectiveness of promotion instruments for the promoted alternative, but also entail different sources of the sales lift. We find that, despite the cannibalization (for the manufacturer: especially in the brand-focused, for the retailer in the retailer-focused decision structures), the above pattern of effects is maintained - both the manufacturer and the retailer incur larger net benefits from discounts, and especially flyer ads, among the more brand-focused households.

Fourth, who wins the most, and how does that depend on the consumers' decision structure? On the whole, the manufacturer appears to reap the highest net promotion benefits. Even in settings with disproportional within-brand-switching, the absolute net sales gains of the manufacturer exceed, or at least match, those of the retailer in the majority of categories. Hence, whereas the decision routes strongly shape the (difference in) effectiveness of store flyer ads and price cuts, they do not dictate who gains most from the promotion – manufacturers often still benefitting more despite brand cannibalization.

3.6.2. Implications

Our results have several implications. First, they shed further light on the role and interplay of different promotion instruments. Consumers for whom brand choice supersedes store choice appear to be purposefully cross-shopping for the best brand offer, as they are responsive to both the announcements in store flyer ads and the depth of the discount. Consumers who mainly trade off different brands from the category inside the store, are not only less influenced by feature ads for most categories but, perhaps surprisingly, also less sensitive to (the depth of) in-store price cuts. This may be so because they are more convenience than price-oriented (reacting to signals of the promotion presence rather than processing the discount depth) or because, given that they are already inside the store, switching to the promoted alternative comes at no extra transaction cost and even a small price cut is thus advantageous. On the whole, it seems that *both* instruments work (better) in one decision structure than the other – a pattern that appears particularly prevalent for less-frequently bought items. A tentative implication is that, especially in such categories, deeper price cuts and store flyer announcements should be used jointly, rather than as alternative/alternating mechanisms.

Given that both manufacturers and retailers seem to enjoy higher net promotion response among brand-focused households, a relevant question is whether such households can be targeted. Exploratory regressions suggest that there is a link between (i) the household' propensity to use a retailer-focused as opposed to brand-focused decision structure (as measured by the contribution of that decision structure to the household's overall choice probabilities) and

(ii) their shopper characteristics as indicated in the conceptual part.[25] On the whole, we find that a retailer-focus is more common among smaller and higher-income households. We also find that these households are less brand-loyal (which underscores the face validity of our results), and tend to be light (and, thus, possible less-involved) category users who are less inclined to plan their purchases in advance. When it comes to promo-related characteristics, these retailer-focused households – though neither more nor less price-conscious – report lower readership of store flyers yet a higher interest in store loyalty programs. Finally, time constraints lead up to a stronger store-focus only for the frequently-purchased categories in our set. Clearly, the opposite profile will pertain to brand-focused households, and managers may use these exploratory insights to tailor their promotions to this more-responsive segment.

Finally, by shedding light on who is likely to gain most (in which type of decision setting), these outcomes may feed into the promotion negotiation process – suggesting who should bear the promotional costs. We find that, overall, the manufacturer appears to enjoy the larger net gains - in line with earlier findings from Srinivasan et al. (2004). At the same time, this does not hold in all settings and categories: especially among more brand-focused households, the retailer may reap comparable benefits from store flyer ads – an insight manufacturers may bring to the negotiation table.

3.6.3. Limitations and Future Research

While our study provides new insights, it also opens up new research opportunities.

First, we considered the decision routes' promotion effects conditional on a category purchase, and hence only documented differential shifts in brand-store choice. Though we expect these to be the most distinct, it is possible that consumers' decision structures also influence their

[25] Please see Appendix 3.B for a detailed exposition on this analysis.

category-purchase incidence and hence trigger different stockpiling effects – something we leave for future study.

Second, from a methodological perspective, though our GEV model is already quite flexible, further refinements may be called for. For one, while we allowed for different promotion effectiveness *between* the two different decision structures, we used common coefficients across brands within each focus. Though this is not uncommon in the literature (e.g. Ailawadi et al. 2007; Foubert and Gijsbrechts 2007; Zhang and Wedel 2009), allowing for differential parameters across brand types may be a fruitful extension. When it comes to store choice, a nested structure that distinguishes traditional supermarkets from hard discounters may be called for, if there is sufficient variety within hard discounters to allow for such as a structure. Last but not least, it may be instructive to make the allocation parameter brand- and/or retailer-specific, or a function of brand/retailer characteristics, and thereby allow stronger or weaker brands or chains to involve different decision structures.

Third, for reasons of tractability, we only considered a limited number of categories, and estimated the models separately for each category, using a random sample of panel members. Unfortunately, this implies that we have only a limited number of households in common for the different categories. Future analyses could estimate and compare the decision patterns by household across categories, and, for that matter, expand the number of categories.

Fourth, though we relied on behavioral data to infer consumers' decision routes, it may be instructive to combine and verify the outcomes of the GEV models with more direct (survey) measures on the underlying process. Ideally, such data should be collected not only at the level of the category or household, but allow for idiosyncratic behaviors for household-category combinations.

Fifth, our dataset does not include information on in-store advertising. As feature and/or discounts can be supported by a retailer using in-store advertising, information on in-store advertising could aid in explaining their effects.

Finally, from a managerial standpoint, the heterogeneity of decision routes and associated promotion effects offers opportunities for targeting, but also raises new issues. For one, the mixture of decision patterns, which are driving the promotional outcomes, differs across categories, and more insights are needed into the underlying category drivers. Also, though we provide preliminary insights into household factors driving the decision structures, further profiling of the segments of shoppers that differ in their decision routes for particular categories is a fruitful next step. Finally, not only category and shopper differences, but also shopping *trip* characteristics may shape consumers' decision routes and promotion responsiveness. Future studies could track how decision structures vary with the type of shopping trip, such as its timing, size, location relative to the household's home or work, and type of format/channel – offering opportunities for trip-based segmentation and targeting of promotional offers.

Table 3.1: Variables and Operationalization

	Variable Name	Operationalization
Controls	*State Dependence Retailer*	Dummy equal to 1 if household's last purchase in the category occurred at the same retailer, and 0 otherwise
	State Dependence Brand	Dummy equal to one if same brand was purchased on household's last purchase in the category, and zero otherwise
	Assortment	Number of SKUs in the brand's line at the retailer (prior moving average of number of SKUs encountered in the panel, over 26 weeks
	Price	Average price per unit volume (across SKUs) for a brand in a given week, as observed in the panel data. Missing observations were replaced by four-week moving average of the brand price at the same retailer, outliers (>5 SD) were replaced by series mean
	Distance	Log-transformed distance (in km) of household to closest outlet of each retailer (updated quarterly)
	Retailer Share (hh)	Household-specific retailer share of visits in initialization period
	Retailer Attraction	The mean-centered promotion pressure across categories for each retailer, weighted by category and retailer share (in initialization period) of each household
Promotion variables	*Feature*	Dummy equal to 1 if there was a feature promotion for (more than half of the brand's SKU line) at the retailer in that week, and 0 otherwise
	Discount	Difference between the brands' regular and promotion price, where promotion prices are identified as prices more than one standard deviation below the mean

Table 3.2: Categories Under Study[a]

	Number of brands	Numbers of alternatives across all 8 chains	Number of purchases	Average number of purchases	Average number of different products	Average number of different brands	Average number of different retailers	Category importance (mean % of total sales within retailer)
Chips	9	25	28682	96	5.59	3.88	3.19	.44
Coffee	9	25	19225	64	4.42	3.16	2.98	1.55
Beer	13	52	15819	53	6.04	4.10	2.90	1.82
Frozen Pizza	7	20	10633	35	4.05	3.04	2.54	.32
Ketchup	9	31	4708	16	3.54	2.69	2.29	.10
Mayonnaise	10	35	6545	22	3.89	2.95	2.37	.11
Muesli	13	31	8368	28	3.76	3.16	2.47	.15
Liquid Detergent	13	46	5365	18	4.37	3.49	2.42	.40
Kitchen Tissue	16	39	6349	21	3.74	3.46	2.40	.28

[a]: Three other originally considered categories, corn flakes, soft drinks and custard, were removed after all, because the large number of brands (soft drinks) or low number of purchase observations (corn flakes, custard) led to unstable and face-invalid estimates.

Table 3.3: Category Descriptives

Panel A: Price and Market Share - Frequently Purchased Food Categories

	Chips				***Coffee***				***Beer***				***Frozen Pizza***			
	Ret 1	*Ret 2*	*Ret 3*	*Mean*	*Ret 1*	*Ret 2*	*Ret 3*	*Mean*	*Ret 1*	*Ret 2*	*Ret 3*	*Mean*	*Ret 1*	*Ret 2*	*Ret 3*	*Mean*
Price NB 1	66.34	59.41	51.03	58.69	303.06	294.27	285.80	289.42	90.72	74.01	73.75	77.70	237.78	225.32	237.81	223.87
Price NB 2	149.72	130.47	146.36	141.11	250.75	236.62	226.40	235.13	64.17	60.93	58.48	61.35	254.36	238.12	216.15	229.06
Price NB 3									73.71	75.71	71.48	74.31				
Mean Price NB	87.32	76.60	88.22		269.92	251.17	252.53		67.49	68.97	65.79		208.18	200.21	200.01	
Share NB 1	.50	.59	.61	.52	.36	.55	.57	.44	.19	.18	.10	.15	.70	.71	.78	.56
Share NB 2	.19	.13	.10	.12	.02	.07	.07	.05	.12	.17	.13	.14	.01	.10	.26	.15
Share NB 3									.16	.22	.16	.14				
Retailer Share	.25	.16	.08		.27	.12	.06		.21	.15	.07		.26	.15	.07	

Panel B: Price and Market Share - Non-Frequently Purchased Food Categories

	Ketchup				*Mayonnaise*				*Muesli*			
	Ret 1	*Ret 2*	*Ret 3*	*Mean*	*Ret 1*	*Ret 2*	*Ret 3*	*Mean*	*Ret 1*	*Ret 2*	*Ret 3*	*Mean*
Price NB 1	.35	.32	.31	.33	164.16	151.09	144.75	153.17	281.06	241.27	252.80	255.81
Price NB 2	.30	.29	.27	.29	73.46	56.80	54.63	56.91	281.66	277.72	226.09	258.99
Price NB 3	.21	.21	.21	.21	121.01	109.52	107.41	113.82	301.92	282.54	274.65	285.40
Mean Price NB	.25	.26	.25		120.28	112.95	111.69		251.52	220.14	212.06	
Share NB 1	.38	.29	.31	.38	.36	.46	.40	.34	.41	.32	.33	.34
Share NB 2	.21	.26	.53	.21	.20	.19	.20	.07	.08	.05	.10	.07
Share NB 3	.07	.13	.06	.07	.06	.06	.11	.04	.04	.05	.05	.04
Retailer Share	.19	.13	.09		.26	.13	.10		.29	.13	.08	

Panel C: Price and Market Share - Non-Food Categories

	Liquid Detergents				*Kitchen Tissue*			
	Ret 1	*Ret 2*	*Ret 3*	*Mean*	*Ret 1*	*Ret 2*	*Ret 3*	*Mean*
Price NB 1	519.68	498.32	535.30	481.58	275.29	279.96	193.63	257.09
Price NB 2	663.69	598.06	636.03	599.77	298.23	174.44	227.15	259.79
Price NB 3	519.47	469.39	466.41	463.98	360.25	319.93	261.07	304.95
Mean Price NB	506.25	459.54	457.63		245.41	212.59	170.65	
Share NB 1	.28	.27	.18	.20	.24	.33	.08	.14
Share NB 2	.23	.22	.26	.19	.08	.03	.07	.07
Share NB 3	.08	.09	.04	.06	.08	.01	.06	.07
Retailer Share	.27	.11	.06		.23	.12	.06	

Panel E: Promo Characteristics - Frequently Purchased Food Categories

	Chips			*Coffee*			*Beer*			*Frozen Pizza*		
	Ret 1	*Ret 2*	*Ret 3*	*Ret 1*	*Ret 2*	*Ret 3*	*Ret 1*	*Ret 2*	*Ret 3*	*Ret 1*	*Ret 2*	*Ret 3*
Promo likelihood[a] NB 1	.08	.10	.00	.15	.18	.00	.21	.17	.14	.17	.11	.17
Promo likelihood NB 2	.15	.14	.22	.01	.01	.02	.09	.14	.11	.00	.05	.12
Promo likelihood NB 3							.10	.12	.18			
Likelihood of a feature at retailer[b]	.23	.24	.22	.16	.20	.02	.80	.92	1.29	.17	.16	.17
Mean Discount NB 1	.18	.40	.26	.18	.20	.08	.77	.73	.82	.25	.25	.19
Mean Discount NB 2	.35	.47	.39	.10	.07	.09	.48	.59	.43	.78	.63	.20
Mean Discount NB 3							.56	.70	.65			

[a]: Likelihood of a promotion for the focal brand in any given week at the focal retailer.

[b]: Likelihood of a promotion of any of the NBs or PLs included in the category in a given week.

Panel F: Promo Characteristics - Non-Frequently Purchased Food Categories

	Ketchup			*Mayonnaise*			*Muesli*		
	Ret 1	*Ret 2*	*Ret 3*	*Ret 1*	*Ret 2*	*Ret 3*	*Ret 1*	*Ret 2*	*Ret 3*
Promo likelihood[a] NB 1	.02	.00	.03	.03	.04	.02	.06	.07	.06
Promo likelihood NB 2	.01	.01	.01	.00	.00	.02	.03	.02	.06
Promo likelihood NB 3	.08	.04	.06	.06	.06	.03	.03	.02	.03
Likelihood of a feature at retailer[b]	.11	.06	.10	.11	.10	.08	.12	.11	.15
Mean Discount NB 1	.15	.16	.16	.12	.28	.08	.25	.18	.15
Mean Discount NB 2	.09	.10	.05	.07	.07	.11	.42	.55	.24
Mean Discount NB 3	.18	.28	.13	.19	.45	.19	.27	.19	.07

[a]: Likelihood of a promotion for the focal brand in any given week at the focal retailer

[b]: Likelihood of a promotion of any of the NBs or PLs included in the category in a given week.

Panel G: Promo Characteristics - Non-Food Categories

	Liquid Detergents			*Kitchen Tissues*		
	Ret 1	*Ret 2*	*Ret3*	*Ret 1*	*Ret 2*	*Ret3*
Promo likelihood[a] NB 1	.15	.19	.13	.09	.12	.03
Promo likelihood NB 2	.19	.19	.18	.09	.04	.02
Promo likelihood NB 3	.22	.13	.14	.05	.00	.00
Likelihood of a feature at retailer[b]	1.22	.79	.96	.25	.17	.07
Mean Discount NB 1	.28	.43	.65	.34	.66	.25
Mean Discount NB 2	.47	.54	.60	.78	.95	.55
Mean Discount NB 3	.47	.41	.45	.44	.25	.62

[a]: Likelihood of a promotion for the focal brand in any given week at the focal retailer

[b]: Likelihood of a promotion of any of the NBs or PLs included in the category in a given week.

Table 3.4: Overview of Models

	Model	*Nesting Structure*	*-2LL*	*BIC*	*# parameters*
Chips	MNL	-	54058	54633	56
	NL	Retailer	53643	54228	57
	NL	Brand	53710	54295	57
	GEV	Brand + Retailer	51259	52439	115
Coffee	MNL	-	38345	38897	56
	NL	Retailer	38020	38582	57
	NL	Brand	38276	38838	57
	GEV	Brand + Retailer	36928	38062	115
Beer	MNL	-	53463	54082	64
	NL	Retailer	53506	54134	65
	NL	Brand	53393	54021	65
	GEV	Brand + Retailer	51823	53090	131
Frozen Pizza	MNL	-	23816	24298	52
	NL	Retailer	23606	24098	53
	NL	Brand	23722	24213	53
	GEV	Brand + Retailer	23059	24051	107
Ketchup	MNL	-	14572	15063	58
	NL	Retailer	14452	14951	59
	NL	Brand	14567	15066	59
	GEV	Brand + Retailer	14180	15186	119
Mayonnaise	MNL	-	18103	18612	58
	NL	Retailer	17952	18470	59
	NL	Brand	18080	18599	59
	GEV	Brand + Retailer	17458	18503	119
Muesli	MNL	-	19823	20383	62
	NL	Retailer	19768	20337	63
	NL	Brand	19815	20384	63
	GEV	Brand + Retailer	19123	20270	127
Liquid Detergents	MNL	-	17008	17559	64
	NL	Retailer	16930	17490	65
	NL	Brand	16984	17544	65
	GEV	Brand + Retailer	16345	17474	131
Kitchen Tissue	MNL	-	15951	16547	68
	NL	Retailer	15710	16314	69
	NL	Brand	15912	16516	69
	GEV	Brand + Retailer	14899	16116	139

Table 3.5: Estimation Results

Panel A: Retailer Focus

		Chips		Coffee		Beer		Frozen Pizza		Ketchup		Mayonnaise		Muesli		Liquid Detergents		Kitchen Tissue		Overall significance
		β	t	β	t	β	t	β	t	β	t	β	t	β	t	β	t	β	t	Z-Value
Controls	**State Dep. Retailer**	0.28	4.38	1.38	35.08	1.63	33.63	0.82	11.55	1.63	13.31	0.13	1.26	0.24	2.40	2.99	20.26	1.36	13.45	45.11
	State Dep. Brand	0.42	10.78	1.80	31.06	1.46	17.55	0.45	9.69	0.55	3.96	0.20	4.69	0.06	1.72	1.97	13.01	0.58	5.82	44.45
	Assortment	0.02	3.14	0.01	1.03	0.00	0.16	0.03	2.56	-0.02	1.09	0.09	4.23	0.13	6.83	0.08	1.56	0.08	4.11	12.67
	Price	-0.23	2.62	-0.72	6.01	-0.07	1.40	-0.40	2.59	-0.06	1.22	-0.04	0.63	0.06	0.53	-0.15	3.73	0.00	0.08	-6.53
	Distance	-0.60	26.42	-0.53	24.15	-0.55	20.02	-1.34	21.99	-0.85	11.46	-0.74	12.84	-1.22	17.30	-0.62	8.70	-0.80	11.07	-53.32
	Retailer Share (hh)	3.83	52.88	2.64	40.43	2.29	27.60	2.76	21.98	1.81	10.32	4.46	24.38	3.86	24.02	0.43	2.33	2.63	16.62	65.47
	Retailer Attraction	0.22	0.38	2.39	3.65	0.40	0.51	4.24	3.97	2.19	1.50	1.02	0.79	-3.12	1.89	2.99	1.81	1.36	13.45	21.54
Promotion parameters	**Feature**	0.64	10.67	0.88	15.48	0.72	11.50	0.22	2.89	0.09	1.71	0.13	1.74	0.56	5.03	1.21	11.71	0.18	3.16	31.65
	Discount	0.12	1.50	-0.68	2.00	0.06	1.07	0.88	3.12	0.45	1.74	-0.08	0.44	-0.06	0.16	0.04	0.71	-0.70	3.13	1.15
Model structure parameters	**Nesting par. (retailer)[v]**	-0.60	7.57	-0.42	10.12	-0.41	6.87	-0.85	9.02	-4.16	13.37	-2.33	10.94	-1.41	8.72	-0.53	5.82	-1.42	8.16	-25.64

Panel B: Brand Focus

		Chips		Coffee		Beer		Frozen Pizza		Ketchup		Mayonnaise		Muesli		Liquid Detergents		Kitchen Tissue		Overall significance
		β	t	β	t	β	t	β	t	β	t	β	t	β	t	β	t	β	t	Z-Value
Controls	**State Dep. Retailer**	3.81	17.24	0.20	3.05	0.71	17.72	2.02	21.60	0.71	9.97	0.93	12.70	1.06	16.21	-0.43	3.61	-0.08	0.79	27.99
	State Dep. Brand	3.49	37.96	0.28	4.15	0.81	16.43	1.33	22.72	0.30	4.37	1.42	18.45	2.26	36.64	0.60	6.90	1.21	10.84	53.84
	Assortment	-0.02	1.32	0.08	4.12	0.19	6.68	0.00	0.18	0.20	2.46	0.15	3.18	0.08	2.86	0.07	1.25	0.63	6.80	10.62
	Price	-2.32	9.52	-0.21	1.19	0.05	0.54	-0.90	3.82	-0.93	3.75	-1.01	3.51	-0.70	4.54	-0.39	7.23	0.33	4.86	-8.56
	Distance	-0.11	3.65	-0.60	19.23	-0.82	26.31	-0.50	11.28	-0.67	13.80	-0.68	14.89	-0.47	11.98	-1.08	16.50	-0.66	13.05	-43.96
	Retailer Share (hh)	0.12	1.20	4.94	39.36	3.15	32.47	0.64	4.99	3.45	20.23	1.48	13.29	2.67	20.56	3.33	20.36	3.78	24.73	52.65
	Retailer Attraction	4.33	5.68	-1.59	1.81	0.92	1.60	2.62	2.19	0.54	0.43	0.61	0.61	3.82	4.09	1.63	1.18	1.14	1.03	18.12
Promotion parameters	**Feature**	1.07	11.48	0.57	5.64	1.44	20.62	0.67	7.62	1.34	10.79	1.23	9.34	1.14	10.61	1.34	15.10	1.42	10.08	35.14
	Discount	0.21	1.52	1.21	2.49	-0.01	0.06	0.90	2.27	-0.69	1.12	-0.64	1.46	1.94	5.87	0.01	0.13	0.89	3.15	5.64
Model structure parameters	**Nesting par. (brand)[v]**	-0.63	7.81	-0.12	2.14	-0.10	2.86	-0.54	9.11	0.00	0.00	-0.41	5.90	-0.06	1.30	0.00	0.01	-0.93	3.82	-11.58
	Allocation par.	-3.57	11.22	-2.46	9.17	-1.12	4.48	2.43	6.42	-0.69	1.31	-0.34	0.97	0.42	0.90	-0.89	1.81	-0.79	1.65	-8.47

[a]: Overall significance based on meta-analytic test across coefficients.

[b]: Nesting parameter is log-transformed for estimation purposes.

[c]: Allocation parameter is estimated using a logit transformation: $\tau_1 = \frac{\exp(\rho)}{\exp(1+\rho)}$, with ρ reported.

Table 3.6: Overview of Decision Patterns[a]

	Retailer focus		Brand focus	
	Importance of decision structure	*Nesting Parameter*	*Importance of decision structure*	*Nesting Parameter*
Chips	51%	0.552*	49%	0.531*
Coffee	59%	0.660*	41%	0.886*
Beer	54%	0.661*	46%	0.905*
Frozen Pizza	56%	0.427*	44%	0.581*
Ketchup	30%	0.016*	70%	1.000
Mayonnaise	47%	0.097*	53%	0.662*
Muesli	33%	0.245*	67%	0.941
Liquid Detergents	41%	0.590*	59%	1.001
Kitchen Tissue	37%	0.241*	63%	0.395*

[a]: Table entries indicate average probability contribution of the decision structure and nesting parameter for both decision structures.

*: significantly different from 1, based on a sign test on the simulated distribution of the nesting parameter, p<.05.

Table 3.7: Feature and Discount Effects by Category and Decision Structure: Promoted Alternative[a]

Panel A: Feature Effect

	Retailer Focus[a]	**Brand Focus[a]**	**Total[b]**
Chips	.97**	.67**	1.64
Coffee	1.12**	.24**	1.36
Beer	.75**	1.08**	1.83
Frozen Pizza	.27**	1.11**	1.39
Ketchup	.02*	1.9**	1.92
Mayonnaise	.2*	1.9**	2.1
Muesli	.14**	1.19**	1.33
Liquid Detergents	.91**	1**	1.91
Kitchen Tissue	.14**	1.0**	1.14

[a]: Column entries give the change in probability contribution relative to the no-promotion setting, for each decision structure, in absolute terms (percentage points).

[b]: Total probability change

*: change significantly positive at p<.10; **: change significantly positive at p<.05 (based on the promotion instrument's parameter estimate in Table 3.4).

Panel B: Discount Effect

	Retailer Focus[a]	**Brand Focus[a]**	**Total[b]**
Chips	0.08	0.04	0.12
Coffee	-0.22	0.2*	-0.02
Beer	0.02	0	0.02
Frozen Pizza	0.5	0.4**	0.9
Ketchup	0.25*	-0.21	0.04
Mayonnaise	-0.04	-0.19	-0.23
Muesli	-0.02	0.57**	0.55
Liquid Detergents	0.01	0	0.01
Kitchen Tissue	-0.16**	0.16**	0

[a]: Column entries give the change in probability contribution relative to the no-promotion setting, for each decision structure, in absolute terms (percentage points).

[b]: Total probability change, across the two decision structures

*: change significantly positive at p<.10; **: change significantly positive at p<.05 (based on the promotion instrument's parameter estimate in Table 3.4).

Table 3.8: Comparison of Net Manufacturer and Retailer Gains from Discount and Feature[a]

Panel A: Feature Effect

	Decision Structure: Retailer Focus[a]				**Decision Structure: Brand Focus[a]**			
	Focal Brand_Retailer Alternative	*Focal Brand*	*Focal Retailer*	*(Focal Brand-Focal Retailer) / (Focal Brand_Retailer Alternative)*	*Focal Brand_Retailer Alternative*	*Focal Brand*	*Focal Retailer*	*(Focal Brand-Focal Retailer) / (Focal Brand_Retailer Alternative)*
Chips	.97	.77	.35	0.43	.67	.49	.49	0.00
Coffee	1.12	.76	.83	-0.06	.24	.19	-.01	0.83
Beer	.75	.62	.2	0.56	1.08	.92	.82	0.09
Frozen Pizza	.27	.09	.03	0.22	1.11	.79	.92	-0.12
Ketchup	.02	-.09	-.19	5.00	1.9	1.54	1.79	-0.13
Mayonnaise	.2	.09	-.2	1.45	1.9	1.29	1.52	-0.12
Muesli	.14	.11	-.03	1.00	1.19	.97	.87	0.08
Liquid Det.	.91	.8	.57	0.25	1	.89	.64	0.25
Kitchen Tissue	.14	.11	-.03	1.00	1.0	.95	.77	0.18

[a:] Entries give the absolute probability increase/decrease of national brand – traditional retailer alternatives for both the Retailer and Brand focus. (The calculations are done for each national brand – traditional retailer combination in the category, and then averaged). Within each decision structure/focus, the "Focal Brand_Retailer Alternative*"* indicates the (average) lift for the promoted brand-store combination, the "Focal Brand" column indicates the (average) net result for the promoting manufacturer (total for the brand across retailers) and the "Focal Retailer" column indicates the (average) net outcome for the promoting retailer (total category change within retailer). "(Focal Brand -Focal Retailer)/(Focal Brand_Retailer Alternative)" then represents the difference in share gain between the promoting manufacturer (column 2) and retailer (column 3), expressed as a fraction of the focal alternative's promotion lift (column 1). For instance, the entry '.43" for chips in panel A, implies that on average, the manufacturer reaps higher net gains than the retailer (the number is positive), and that the size of this net-gain difference is about 40% of the absolute lift for the promoted brand-store combination.

Panel B: Discount Effect

	Decision Structure: Retailer Focus[a]				**Decision Structure: Brand Focus[a]**			
	Focal Brand_Retailer Alternative	*Focal Brand*	*Focal Retailer*	*(Focal Brand -Focal Retailer) / (Focal Brand_Retailer Alternative)*	*Focal Brand_Retailer Alternative*	*Focal Brand*	*Focal Retailer*	*(Focal Brand-Focal Retailer) / (Focal Brand_Retailer Alternative)*
Chips	0.08	0.07	0.04	0.38	0.04	0.03	0.03	0.00
Coffee	-0.22	-0.17	-0.21	-0.18	0.2	0.19	0.17	0.10
Beer	0.02	0.02	0.01	0.50	0	0	0	-
Frozen Pizza	0.5	0.39	0.23	0.32	0.4	0.24	0.3	-0.15
Ketchup	0.25	0.25	0.1	0.60	-0.21	-0.18	-0.17	0.05
Mayonnaise	-0.04	-0.03	0.02	1.25	-0.19	-0.13	-0.15	-0.11
Muesli	-0.02	-0.04	-0.07	-1.50	0.57	0.47	0.43	0.07
Liquid Det.	0.01	0.01	0.01	0.00	0	0	0	-
Kitchen Tissue	-0.16	-0.16	-0.06	0.63	0.16	0.15	0.13	0.13

[a:] Entries give the absolute probability increase/decrease of national brand – traditional retailer alternatives for both the Retailer and Brand focus. (The calculations are done for each national brand – traditional retailer combination in the category, and then averaged). Within each decision structure/focus, the "Focal Brand_Retailer Alternative" indicates the (average) lift for the promoted brand-store combination, the "Focal Brand" column indicates the (average) net result for the promoting manufacturer (total for the brand across retailers) and the "Focal Retailer" column indicates the (average) net outcome for the promoting retailer (total category change within retailer). "(Focal Brand -Focal Retailer)/(Focal Brand_Retailer Alternative)" then represents the difference in share gain between the promoting manufacturer (column 2) and retailer (column 3), expressed as a fraction of the focal alternative's promotion lift (column 1). For instance, the entry '.38" for chips in panel A, implies that on average, the manufacturer reaps higher net gains than the retailer (the number is positive), and that the size of this net-gain difference is about 38% of the absolute lift for the promoted brand-store combination.

Appendix 3.A: Estimation Results for Beer

	Structure 1				Structure 2			
Variable	*Mean*	*T value*	*SD*	*T value*	*Mean*	*T value*	*SD*	*T value*
State Dependence Retailer	1.63	33.63	-0.96	19.82	0.70	17.71	-0.15	4.73
State Dependence Brand	1.46	17.55	0.24	6.74	0.81	16.43	0.76	19.28
Assortment	0.00	0.16	-0.08	4.03	0.19	6.68	-0.09	3.90
Price	-0.07	1.40	0.00	0.06	0.05	0.54	0.28	4.17
Distance	-0.55	20.02	0.15	5.72	-0.82	26.31	-0.45	16.23
Retailer share hh	2.28	27.60	-1.40	21.36	3.15	32.47	-0.85	15.83
Retailer attraction	0.40	0.51	-1.78	2.11	0.92	1.60	1.06	1.64
Feature	0.72	11.50	0.64	11.97	1.43	20.62	0.18	2.88
Discount	0.06	1.07	0.01	0.18	-0.01	0.06	-0.79	6.33
Brand constant: #1	-0.21	3.00	0.60	10.02	-1.46	6.28	3.22	19.59
Brand constant: #2	-0.33	4.89	0.08	1.26	-0.60	4.15	2.08	25.10
Brand constant: #3	-0.21	2.85	1.01	12.28	-0.11	0.89	0.58	7.46
Brand constant: #4	-0.64	6.13	-1.12	12.06	-2.30	6.16	0.10	0.40
Brand constant: #5	-1.06	5.74	0.74	5.39	-3.17	3.88	1.81	3.95
Brand constant: #6	-1.94	6.32	-1.04	6.26	-2.01	6.99	-0.28	1.18
Brand constant: #7	-0.84	7.77	-0.21	2.37	-3.52	6.36	2.18	8.39
Brand constant: #8	-1.07	6.82	0.35	2.73	-1.65	6.42	1.73	13.02
Brand constant: #9	-1.33	7.08	0.87	6.91	-4.56	4.66	-2.04	6.49
Brand constant: #10	-1.04	5.79	-0.50	3.81	-0.11	0.80	-1.88	25.79
Brand constant: #11	1.83	10.19	0.18	0.99	2.09	7.68	2.01	14.82
Brand constant: #12	-1.94	2.56	-3.19	7.22	4.15	23.83	0.88	15.09
Brand constant: #13	-0.65	1.51	-0.73	1.63	2.21	10.14	1.05	9.57
Brand constant: #14	0.70	5.83	-0.85	5.89	1.25	6.24	-1.31	11.98
Brand constant: #15	0.73	9.21	0.47	6.04	1.42	7.44	-2.70	20.20
Brand constant: #16	-0.20	0.60	-0.58	1.98	1.71	12.13	0.05	0.38
Brand constant: #17	1.05	11.29	-0.42	8.78	1.33	7.99	-0.18	1.21
Brand constant: #18	0.82	9.90	-0.50	10.13	-1.19	1.54	-1.94	5.01
Retailer constant: #1	0.33	2.72	0.84	8.10	0.07	0.52	-0.03	0.36
Retailer constant: #2	0.66	6.01	-0.89	17.49	-0.60	4.45	-0.89	15.70
Retailer constant: #3	-0.68	4.18	0.33	1.98	-0.17	1.22	1.44	19.99
Retailer constant: #4	-0.14	0.99	-1.27	14.86	-0.49	3.08	-0.78	9.76
Retailer constant: #5	0.26	2.19	-0.93	13.75	0.11	0.87	0.47	10.77
Nesting Parameter	-0.41 (t-value = 6.87)				-0.10 (t-value = 2.86)			
Tau	-1.12 (t-value = 4.48)							

* Estimation results for Beer category. First author can be contacted for estimation results of all other categories.

Appendix 3.B: The link between Decision Patterns and Shopper Characteristics

To explore whether households with different decision structures can be profiled, we proceed as follows. In each category, we first obtain the posterior utility-function parameters for each household, as described in (Train 2009). Next, we use these parameters to calculate the portion of the households' choice probabilities accounted for by the retailer-focused decision structure (i.e. the ratio of $P_{h,br.t|d_{retailer}}$ / $P_{h,br.t}$). Because this number may vary across purchase occasions within a household, we calculate the average as well as the standard deviation across choice alternatives and trips.

In each category, we then run a weighted least squares regression, with the households' average choice-probability portion in the retailer-focused decision structure as the dependent variable, the inverse of the households' standard deviation (of the allocation parameter, τ) as weight, and a number of household-related drivers obtained from GfK's panel-member survey as explanatory variables. Specifically, from the GfK survey, we retained a number of household characteristics potentially related to households' brand or store focus. We then factor-analyzed these characteristics (retaining 8 factors with an eigenvalue higher than or close to one that were easy to interpret), and retained a representative (the highest-loading) characteristic for each factor. The latter characteristics were used as explanatory variables in the regression, to which we added the household's category use rate as a separate driver – as shown in Table 3.A.1 (Details on the measures can be obtained on request). The table also reports the regression coefficients for each category, next to a meta-analytic significance test across categories. Combined significance across categories is determined using a meta-analytic test of adding weighted Z's (with weights equal to the sample size of the categories; Rosenthal 1991).

Table 3.A.1: Impact of Shopper Characteristics on Prevalence of Decision Structures

	Chips		Coffee		Beer		Frozen Pizza		Ketchup		Mayonnaise		Muesli		Liquid Detergents		Kitchen Tissue		Overall significance	
	β	P	β	P	β	P	β	P	B	P	β	P	β	P	β	P	β	P	Tested sign	P
Constant	0.85	0.00	1.19	0.00	2.03	0.00	-0.01	0.96	-0.53	0.01	0.55	0.00	-0.45	0.00	0.86	0.02	1.19	0.00		
Price consciousness	0.07	0.02	0.05	0.00	0.03	0.31	0.06	0.10	-0.20	0.00	0.19	0.00	0.00	0.96	0.17	0.01	0.05	0.00	+	0.14
Household Size	-0.13	0.00	-0.02	0.31	0.06	0.01	0.16	0.00	-0.11	0.00	-0.08	0.00	0.01	0.11	-0.14	0.00	-0.02	0.31	-	0.00
Brand commitment	-0.03	0.42	-0.07	0.10	-0.13	0.00	-0.09	0.04	0.36	0.00	0.03	0.23	-0.03	0.15	-0.28	0.00	-0.07	0.10	-	0.00
Loyalty Program Interest	0.16	0.00	-0.12	0.00	-0.09	0.07	0.06	0.06	0.11	0.00	-0.03	0.45	0.11	0.00	0.35	0.00	-0.12	0.00	+	0.00
Income	0.04	0.00	-0.01	0.00	0.03	0.00	-0.01	0.19	0.03	0.00	0.03	0.00	-0.01	0.21	-0.01	0.15	-0.01	0.00	+	0.00
Degree of Planning	-0.44	0.00	0.09	0.05	-0.17	0.17	-0.08	0.07	0.35	0.00	0.14	0.00	-0.07	0.00	-0.02	0.79	0.09	0.05	-	0.05
Store Flyer Readership	0.00	0.46	0.00	0.14	-0.02	0.02	0.02	0.03	-0.02	0.00	-0.01	0.01	0.01	0.00	-0.03	0.00	0.00	0.14	-	0.00
Time Pressure	0.10	0.12	0.05	0.02	-0.03	0.61	0.15	0.01	-0.33	0.00	-0.26	0.00	0.13	0.00	0.04	0.56	0.05	0.02	+	0.53
Category use rate	0.00	0.79	0.00	0.21	-0.01	0.00	0.00	0.00	0.00	0.03	0.00	0.02	0.00	0.06	-0.01	0.00	0.00	0.21	-	0.00

Chapter 4

Retailer Savings Weeks: The New Promotional Mantra?

4.1. Introduction

A recent and as of yet largely unstudied phenomenon in grocery retailing is the use of "Savings Weeks", i.e. large scale promotional events in which supermarket chains advertise promotions across multiple categories simultaneously, under a common theme, and across several weeks. These promotional events shift the focus away from business-as-usual discounts on particular products; towards "unusual" savings opportunities on the entire shopping basket purchased at the retailer. Examples are Belgian retailer Delhaize's "Crazy Prices Event", Kroger's "Cart Buster Savings Event" during which the American retailer claims to offer over $100 in savings on a set of products; or leading Dutch retailer Albert Heijn (a subsidiary of Ahold)'s "Hamsterweken", which entice consumers to massively buy groceries in bulk and stock them up at home through a broad set of 'buy-one-get-one-free' offers, renewed each week, over consecutive weeks.

Through such events, retailers hope to revive their customer base (i.e. attract extra visitors to the store), and increase current customers' spending at the store (Garstenveld 2015). Indeed, by advertising the promotions as store-wide deals and integrating them under a common theme, the events may generate extra attention and signal unusual bargain-opportunities, both to consumers who otherwise would or would not visit the store. Still, several caveats arise. For instance, the question remains whether newly attracted visitors will be retained in post-event weeks, when the retailer's promotional activity returns to 'business-as-usual'. Or, the store-wide and uniformly-tagged promotions may direct more of the consumers' basket towards (stocking up) promoted items, thereby dampening the amount spent - especially in weeks following the event. Hence, though anecdotal evidence suggests that traffic and basket-size increases do come about during the event period (e.g. Bijlsma 2009; Garstenveld 2015), industry analysts express doubts about the net outcomes of these large-scale "Savings Week" events (Meijsen 2014; Rooijers 2014; van Der Werf 2013).

A rigorous analysis of the countervailing forces is currently lacking, and this sets the stage for our current research. Specifically, we aim to address the following questions. First, how do large scale "Savings Week" events at grocery chains affect store traffic and spending during promotion weeks? Do they attract extra visitors to the store? Do they increase current customers' spending at the store? And: to what extent do similar competitive events offset the impact of the retailer's own initiatives? Second, what are the dynamics involved? Do the Savings Weeks, given their 'recurrent' and 'recognizable' character, lead to negative lead effects? Do they come along with post-event dips in store traffic and spending? To answer these questions, we study weekly store visit and spending of a panel of Dutch households, across the top seven grocery chains (of which four engage in Savings Weeks), during a three year period covering 25 Savings Week events (five types/themes, each with several occurrences).

The paper is organized as follows. After a brief review of background literature, we start by describing the "Savings Week" events that are the focus of our study – outlining several of their defining characteristics. Next, we develop a framework for their anticipated effects. We then present the models to test this framework, followed by the empirical estimates. We conclude with summary insights relevant to academics and retail managers.

4.2. Regular versus "Savings Week" Promotion Events

4.2.1. Background

A large body of literature has studied the effect of sales promotions in the consumer packaged goods industry. The literature has mapped out consumer responses to specific (typically brand or SKU-level) promotions and discounts, which often pertain to the re-allocation of purchases over time and location (e.g. Gauri et al. 2008) and looked at the implications for retailers and/or manufacturers (e.g. Srinivasan et al. 2004). In addition, the effect of different types of promotions has been studied, showcasing how consumers react to price discounts (Bijmolt et al. 2005), multi-buy (Foubert and Gijsbrechts 2010) and premium promotions (e.g. d'Astous and Jacob 2002). While the number of papers dealing with sales promotions is impressive, extant literature has predominantly focused on the effect of such promotions in isolation (see van Heerde and Neslin (2008), and Ailawadi et al. (2009) for an excellent discussion). Some studies have documented the impact of loyalty programs (van Heerde and Bijmolt 2005), which grant economic benefits and extra promotional discounts to current store customers (i.e. loyalty card holders), often linked to some 'savings' objective (accumulation of purchases at the store). Others have studied the effect of promotional calendars, i.e. sequence of promotional actions over time by a specific brand or retailer (e.g. Guyt and Gijsbrechts 2014; Mehta and Ma 2012; Silva-Risso et al. 1999; Tellis and Zufryden 1995), or the effect of an increase in number of products on promotion (Volle 2001) on store patronage. Still, as of yet, the impact of large-scale promotional 'events', initiated by a grocery retailer offering multiple discounts under a common ‘Savings Theme’, remains unstudied.[26]

4.2.2. “Savings Week” Promotion Events: Defining Characteristics

“Savings Week” promotion events, as we study them here, differ from HiLo retailers’ regular promotional activities in content, communication, and timing.

As for content, one distinguishing characteristic is that the promotions are presented to consumers under an overarching, unifying “Savings” theme, chosen by and specific to that retailer. Another common aspect of these events is that they promote store-wide savings, i.e. offer deals on a broad range of categories throughout the store. Finally, in many instances, even if the number of items on-deal within these promoted categories is not excessive, the deal-offers are unusually deep, and often quantity-based (e.g. buy-one-get-one-free).

The communication of the promo events also differs from regular promotions. This theme is not just apparent in-store, but supported with increased out-of-store advertising (typically around the start of the campaign). The nation-wide advertising is catered to the specific theme of the Savings week and stresses the (storewide) savings that can be reaped for consumers.

In terms of timing: even though the items promoted under the theme-heading may rotate on a weekly basis, Savings Week events within a given retailer typically extend over a longer period (about three weeks on average, compared to one week for business-as-usual store-flyer promotions). Also, they are recurring events, often once or twice a year, mostly around the same time each year.

[26] Savings weeks share several characteristics with clearance sales. However, there are also important differences, as clearance sales are often aligned with seasonal and/or product cycles (i.e. pertain to products that are near-obsolete) and, hence, often occur simultaneously at all competitors. Also, the savings weeks that we study should be distinguished from promotions where retailers capitalize on the theme and media attention of large-scale exogenous/external events, such as the Olympics (Keller, Deleersnyder and Gedenk 2015).

Because of these characteristics, we expect the impact of such events on store visits and basket sizes to differ from the usual, day-to-day-business retailer promotions - as further developed below.

4.3. Differential Impact of Savings Week Promotion Events

The literature to date has extensively examined how retailers' promotional activities (e.g. price cuts, displays and feature ads) for specific brands/SKUs in specific categories influence their store visits and sales, within and beyond the promotion period (see, e.g. Ailawadi et al. 2009 for an overview). By their very nature, we expect the effects of Savings Week promotion events on store traffic and spending to be more pronounced and potentially different from those of retailers' 'business-as-usual' weekly promotional activity. Below, we explain why.

4.3.1. Immediate Impact during Event Weeks

Traffic. A first, and important, aspect of Savings Week events is that they create extra awareness. The launch of these promotional events is typically supported with increased retailer (TV and print) media advertising featuring the common savings theme of the retailer, which draws more attention than regular promotions, and informs a larger consumer base (who may not consult store flyers or come across the promotions in-store) about big potential savings at the retailer. This is important, because search cost strongly impedes promotional cross-shopping (Gauri et al. 2008), and regular promotions at the store are mostly communicated through store flyers for which readership remains limited (see, e.g., NOM/GFK 2014, reporting that only 18% of the population receives store flyers). Second, Savings Week promotions typically cover items across a wider range of categories, and signal the potential for larger savings on the entire basket than the non-Savings weeks. As such, they are more likely to circumvent threshold effects: they may attract consumers who otherwise would not consider the store, or for whom the offered advantage would not justify the extra shopping effort (e.g. Baltas et al. 2010). While the literature so far pointed to rather weak direct store-switching effects for promotions (Srinivasan et al. 2004), we thus expect Savings Weeks to trigger more important changes in store patronage: a higher level of awareness, combined with larger and easier-to-spot potential savings triggering consumers to redirect their trips towards the promoting store.

Spending. The impact of Savings Week events on visitors' total store spending during promotional weeks is somewhat less equivocal. Of course, for new customers, any amount spent is an increase (even though new visitors may spend less at the store than regular customers, in which case the mean weekly basket size across all visitors may become smaller). For loyal consumers who already visit the store absent the event, weekly spending at the store may go up or down during Savings Weeks. On the one hand, the range of promoted items creates potential for savings across-the-board, and may stimulate (even current) customers to purchase categories at the store they regularly would have bought elsewhere (or not at all) and/or in future periods. Moreover, the fact that these promotions do not appear as separate stimuli, but carry a common theme, may create a "reminder" effect – reinforcing the impression that there are important savings to be reaped in (almost) all categories (Zhang and Breugelmans 2012), and the synergy that arises from increased usage of both mass media and in-store promotions may intensify this effect further (Naik et al. 2005). In addition, consumers can be less incentivised to plan due to the slack generated by the larger savings, which may result in more impulse purchases (Bell et al. 2011; Stilley et al. 2010). Finally, the unusual depth of the discount and/or use of quantity-based promotions during Savings Weeks may stimulate more stockpiling. For instance, similar to Kroger's Cart Buster Savings Event, the tagline for one of these events at a leading Dutch retail chain was:

“Massive Discounts, Massive Stocking”[27], encouraging consumers to stock up (or even hoard) on the products that were on offer. Based on the above, we expect to see an increase in the quantity (i.e. number of categories, and within a category, the number of units) bought.

On the other hand, the vivid announcements or deep offers may produce more-than-usual shifts from non-promoted (or: shallowly-promoted) towards lower-priced promoted items. This is facilitated by the uniform format of the promotions and presentation under a common and easy-to-process savings theme, which makes it easy for the consumer to spot and recognize the deals in-store. Especially coupled with an unusual discount depth, this may dampen current customers’ (increase in) monetary spending. If the increased quantity is offset by large reductions in the prices consumers pay due to large savings, total monetary spending during the Savings Weeks will decrease. Our empirical analysis will shed light on which of the two forces dominates.

4.3.2. Dynamic Effects

Traffic. Even if new customers are attracted to the store during the Savings Weeks, the question remains what will happen in pre- and post-event weeks. On the one hand, new customers may have ‘found their way to the store’ and, having become somewhat familiar with it (in the course of subsequent event-weeks), or realizing its attractive features in-store, may return even after the Savings Weeks are over (van Lin and Gijsbrechts 2014). On the other hand, consumers whose sole objective was to benefit from the temporary deep and easy-to-spot offers, are more likely to renege in the post-promotion period (see, e.g. Gedenk and Neslin 2000). Regular store visitors, from their part, may have a reduced visit propensity in the post-event week because of the built-up inventory.

[27] Albert Heijn supported the “Hamsterweken” in television ads using the slogan: “Grootse korting, groots inslaan” – freely translated to: “Massive Discounts, Massive Stocking”, encouraging consumers to buy in bulk and stock up on the products that were on offer. A literal translation of Hamsterweken would be: Hamster Weeks, referring to the European Hamster that hoards food in storage chambers and hibernates during winter, during which it lives of the food it has hoarded.

Spending. The Savings Week advertisements typically inform consumers about the time frame in which they can benefit from the offers, and urge them to 'benefit NOW'. Hence, consumers are more aware that the larger potential savings are limited to the duration of the promotional event and encouraged to engage in aggressive stockpiling behavior. Though higher inventories may stimulate consumption (Ailawadi et al. 2007; Ailawadi and Neslin 1998; van Maanen 2012), we expect consumers to be left with an unusually high inventory following the event weeks, which may produce deeper post-event dips in spending at the store.[28] Moreover, because the promotional events are recurring, they may come with important lead effects (Neslin and van Heerde 2009). The Savings Week ads 'educate' consumers to capitalize on savings offered during event-weeks and, as consumer learn about the probable event timing, this may produce more pronounced anticipation effects (in the spirit of Sun 2005) and pre-event dips in store level spending. In contrast, promotional cycles for individual categories and brands during regular promotion weeks are less easy to detect and anticipate for consumers.

How will these different forces net out? This is not clear a priori, and we leave it as an empirical issue. In the remainder of the paper, we empirically examine the impact of promo events on households' shopping behavior, after which we will discuss the implications for retailers. In the next section, we present the household-level store visit and spending model.

4.4. Methodology

As indicated above, a Savings Week event has the potential to influence both the decision of a consumer to visit a retailer in a given week, and the basket size at that retailer in that week. Similar to Fox et al. (2004) and Zhang and Breugelmans (2012), we capture these two decisions through a model with two layers. In the first layer, a household (h) decides on

[28] Although the set of promoted SKUs may rotate during these Saving Weeks, households may stock up on multiple categories and thereby still see a drop in total spending in the week following the event. However, the rotation of the set of SKUs may merely shift around expenses during the event weeks.

whether or not to visit a retailer (r) in a given week (w).[29] The second layer models the household's spending level ($y_{r,w}^{h}$), conditional on a visit to the retailer in that week ($v_{r,w}^{h} = 1$). A household may visit multiple retailers: $v_{r,w}^{h}$ equals 1 for all retailers that the household visits. In the spirit of Zhang and Breugelmans (2012), the overall model is given by:

$$y_{r,w}^{h} = \begin{cases} {y_{r,w}^{h}}^{*} & if\ v_{r,w}^{h} = 1 \\ 0 & if\ v_{r,w}^{h} = 0 \end{cases} \tag{4.1}$$

To capture visit incidence, we introduce a latent variable ${v_{r,w}^{h}}^{*}$which is modelled as:

$${v_{r,w}^{h}}^{*} = \alpha_{r}^{h} + x_{r,w}^{h}\zeta^{h} + u_{r,w}^{h} \tag{4.2}$$

where α_{r}^{h}; ζ^{h} are the parameters, $x_{r,w}^{h}$ is a vector of household-, retailer- and/or week-specific drivers of the utility of visiting the store (further specified below), and u_{rw}^{h} is a random component assumed to follow an extreme value distribution. The probability for an individual to visit a retailer in a given week then becomes:

$$P_{r,w}^{h} = \frac{\exp(\frac{\beta^{h\prime}X_{r}^{h}}{\sigma_{r}})}{1 + \exp(\frac{\beta^{h\prime}X_{r}^{h}}{\sigma_{r}})} \tag{4.3}$$

where σ_{r} is a retailer-specific scale parameter. The decision to visit a specific retailer may be correlated with visit decisions for other retailers. To account for the interdependence of retailer patronage within a given week, we use a copula-based approach, as developed by Bhat and Sener (2009). This approach allows us to use a closed-form analytic expression for the joint probability of visiting a set of retailers in a given week. For notational purposes, we re-write equation 4.3 as follows: The joint probability of visiting a set of retailers in a given week for a household is then modelled as follows[30]:

[29] Note that, like Zhang and Breugelmans 2012, we focus on consumers' decision whether or not to visit a retailer in a given week, rather than on their retailer choice given a visit, because large scale events may well affect consumers' trip organization and number of trips (e.g. they may start to spread their grocery purchases across their regular and the promoting store in a given week).
[30] For notational simplicity, we omit the week index.

$$P^h_{(r_1=d_1,r_2=d_2,\dots,r_7=d_7),w} = \left[\prod_{r=1}^{R}\left(\frac{\exp(\frac{\beta^{h\prime}X^h_{rw}}{\sigma_r})*d_r}{1+\exp(\frac{\beta^{h\prime}X^h_{rw}}{\sigma_r})}\right)\right]\left[1+\sum_{r=1}^{R-1}\sum_{k=r+1}^{R}(-1)^{d_r+d_k} * \right.$$

$$\left. \theta_{rk}\left\{1-\left(\frac{\exp(\frac{\beta^{h\prime}X^h_{rw}}{\sigma_r})*d_r}{1+\exp(\frac{\beta^{h\prime}X^h_{rw}}{\sigma_r})}\right)\right\}\left\{1-\left(\frac{\exp(\frac{\beta^{h\prime}X^h_{kw}}{\sigma_k})*d_k}{1+\exp(\frac{\beta^{h\prime}X^h_{kw}}{\sigma_k})}\right)\right\}\right] \quad (4.4)$$

where d_r indicates whether or not the retailer has been visited and subscript *k* denotes a competing retailer. The copula-based approach allows for correlations between pairs of observations, by allowing θ_{rk} to take on unique values for each retailer (*r*,*k*) combination. We allow for three different levels of correlation, based on the format used by the supermarket (Hard Discounter - Hard Discounter, Hard Discounter – Traditional Supermarket, Traditional Supermarket – Traditional Supermarket). Furthermore, we allow for a different scale factor σ_r, based on the format employed by the supermarket (HD or TS). If θ_{qk} takes on the value of 0, expression 4.4 collapses to a heteroskedastic logit. If θ_{qk} equals 0 and σ_r= 1 for all retailers, expression 4.4 collapses to an ordinary logit for each retailer.

Spending in the store, conditional upon a retailer visit by the household in the considered week ($y^h_{r,w}|v^h_{r,w} = 1$), is modelled as follows:

$$y^{h\ *}_{r,w} = \iota^h_r + z^h_{rw}\beta^h + \tau\left(\log\left(P^h_{r,w}\right) + \frac{\left(1-P^h_{r,w}\right)*\log(1-P^h_{r,w})}{P^h_{r,w}}\right) + \varepsilon^h_{rw} \quad (4.5)$$

where $\iota^h_r;\ \beta^h$are parameters to be estimated, z^h_{rw} a vector of household-, retailer- and/or week-specific variables related to expenditures (specified in the next section), and ε^h_{rw} a random component, assumed to be normally distributed: $\varepsilon^h_{rw}\sim N(0,\omega)$. Similar to Krishnamurthi and Raj (1988), we link the visit and spending equations, by using the approach suggested by Dubin and McFadden (1984): we include the term $\left(\tau\left(\log\left(P^h_{r,w}\right) + \frac{\left(1-P^h_{r,w}\right)*\log(1-P^h_{r,w})}{P^h_{r,w}}\right)\right)$ correcting for the non-random occurrence of the store visits to ensure unbiased parameter estimates.[31] The Dubin and McFadden correction term is the analogue to the Inverse Mills Ratio in Heckman correction models for logit models. To accommodate unobserved household heterogeneity, all household-specific parameters follow a normal mixing distribution (the means and standard deviations of which will be assessed). Equations 4.4 – 4.5 are estimated with simulated maximum likelihood, using 100 draws from the mixing distributions.

4.5. Data and Operationalizations

4.5.1. Data

The model is calibrated on GfK panel data comprising household purchases for the period 2009-2011. The dataset contains information on households' purchase histories, as well as weekly information on price levels and promotional activities of all Dutch retailers. In this study, we consider household spending at the top 7 retailers in terms of market share. Table 4.1 provides some descriptive statistics for the considered retailers - which, together, cover about 60% of the Dutch grocery market. We estimate the models using 312 households[32] on 94 weeks of data, ranging from the start of 2010 up to late 2011. On average, a household visits 1.20 retailers in a given week and spends 36.42 euro per visit. Comparison of the chains' relative share in the entire market (panel) and for our estimation sample (subset of households) suggests that our data are quite representative.

--- Insert Table 4.1 about here ---

Table 4.1 further shows that Albert Heijn has by far the highest weekly visit rate (i.e. fraction of weeks with a chain visit, averaged across households), followed by Aldi, C1000 and Lidl.

[31] The Dubin and McFadden term requires individual probabilities for each retailer-week combination. As equation 4 estimates the joint likelihood of visits to all retailers within a given week, we first 'integrate out' the likelihood per retailer.

[32] To keep estimation tractable, we start with a random sample of 500 households from the total set of panel members. We then retain only households that are part of the panel throughout the period 2009-2011 (our initialization plus estimation period), and who do most of their shopping at the included chains.

Weekly spending among store visitors is more comparable across chains, with somewhat higher levels for market leader Albert Heijn, and lower levels for the hard discounters.

4.5.2. Promotion Events: Descriptive Statistics

To identify the promotional weeks that qualify as “Savings Week events”, we combine several sources. We start from a data set containing descriptive information on the events. This data set contains the name of the event as communicated by the retailer in the media,[33] as well as the event timing. Next, we couple these events with retailers’ actual promotional activity. Specifically, we use GfK scanner panel data to calculate, for each retailer-week, the total number of SKUs on offer under promotional conditions, and how this deviates from the regular number of SKUs on deal. We then retain events that carry an overarching theme, run at least twice during our 3-year data period (with a combined duration that exceeds 6 weeks), and have above-normal promotional activity (i.e. mean number of SKUs on promotion during event-weeks at least one standard deviation above the weekly average number of SKUs on promotion at that retailer).[34] Next, we cross-verify this list of events by consulting industry experts. Out of the 6 identified events; five are classified correctly according to experts, while one is considered a ‘loyalty’ event and excluded from our list.[35] All selected events occur at HiLo retailers, whereas EDLP retailers do not have any savings events.

Table 4.2 contains descriptive information on the Savings Week promo events included in our study. On average, a promotional event lasts three weeks, with a maximum of 4 weeks. As can be seen from Table 4.2, promotional events carry more SKUs on themed promotion compared to other weeks within the focal retailer ($p < 0.01$ for all events).

--- Insert Table 4.2 about here ---

[33] Examples of these names, Euroweeks and Hamsterweeks, indicating the goal and theme of these weeks.
[34] Promo events tend to run for multiple weeks on a row. Using a more stringent selection criteria (e.g. 2 standard-deviations) would only leave one promo event.
[35] The event name featured “collect stamps”, a reference towards collecting stamps that can later be used for monetary rewards.

To assess whether and when these promo events are supported by extra retailer advertising, we regress the retailers' weekly advertising spending levels (stacked for the 4 retailers involved in these events), against retailer-specific constants (reflecting the retailers' 'regular' ad spending), as well as time-dummies related to (i) the week prior to the start of an event, (ii) the first event week and (iii) all event weeks. The results show that there is no significant lead-week advertising effect, but advertising is stepped up in the first week of the event (and then lowered during remaining event weeks). Hence, while there do not seem to be pre-announcements for the Saving-Weeks, this points to increased advertising support that peaks in the starting week.

4.5.3. Variables and Operationalization

Our models incorporate several drivers of store visits and spending identified in the literature (see, e.g. Fox et al. 2004; van Heerde et al. 2008). Next to retailer constants, these include a household-specific retailer price index, $price_{rw}^{h}$, (calculated using the weighted average of category-level price indices at that retailer in a given week and the households propensity to purchase from these categories, see Table 4.3), in addition to the sum of the price indices for competing retailers, $comp\_price_{rw}^{h}$, a household-specific retailer assortment variable $assort_{rw}^{h}$ (reflecting the assortment available weighted by household-category importance), the (log of) advertising spending by the retailer ad_spend_{rw}, and the household's log-transformed distance to the nearest retailer outlet $dist_{r}^{h}$ (which we calculate for each household and update quarterly to account for store openings and households that move). To account for seasonality, we include the weekly aggregate cross-store and cross-household visit and expenditure indices; $season\_visits_{w}$ and s$eason_spending_{w}$. Moreover, the visit-incidence model includes a state-dependence variable $last\_visitweeks_{rw}^{h}$ (indicating the number of weeks with a visit by a given household at the focal retailer in the previous four-week period), and a retailer-share variable $ret\_share_{r}^{h}$ (measured as the share of household visits to the focal retailer over the entire observation period, see Zhang and Breugelmans (2012) for a similar operationalization), which controls for multi-store shopping. Likewise, in the retailer spending equation, we include four lagged-spending variables $last\_spending_{r,w-x}^{h}$, to capture carry-over / stockpiling effects, and the average weekly household expenditure at the retailer, $avg\_spending_{r}^{h}$.

--- Insert Table 4.3 about here ---

Next to these controls, we include separate variables related to the Savings Week events. For each of the five events, we include a dummy variable $event_{rw}$ that equals one during event weeks at the retailer (and zero otherwise); and captures the immediate event-effect on retailer visit incidence and spending. An event at a competing retailer can impact visit likelihood through $comp\_event_{rw}$, which equals one if there is a competing event at any of the other retailers during the focal week. Note that, because the price and advertising variables discussed above also include price cuts and media spending during Savings Weeks, the event-dummy and competing-event coefficients capture the 'extra' impact of the Savings Week events, over and above their effect through store-wide price and advertising levels. To allow for a differential event-effect on retailer visit incidence and spending of more vs. less 'customary' store shoppers, we include an interaction variable $ret\_share_{r}^{h} * event_{rw}$ in both equations. A positive (negative) coefficient for this variable signifies that the event more (less) strongly increases visit incidence or spending among regular customers of the store.[36]

--- Insert Table 4.4 and 4.5 about here ---

As for the dynamics, we include a lead dummy $lead\_event_{rw}$, capturing the anticipation effect in the week prior to the promotion event. Moreover, to accommodate that carry-over effects (i.e. the tendency to revisit the store, or the impact of previous on current

[36] We note that even though households may be completely retailer loyal, they can still have an increase in visit propensity if they do not visit the retailer every week.

spending) may be different for shoppers intercepted during the event, we also include a variable $lag\_event\_visit_{rw}^{h}$ in the visit-incidence equation that is activated only in the post-event week (zero otherwise), and takes on the value of 1 for households that visited the retailer during the promotional event. Similarly, we add a variable $lag\_event\_spend_{rw}^{h}$ in the expenditure equation that equals the total expenditure at the retailer during event weeks, in the post-event week; and zero in all other weeks. Because these variables operate over and above the 'regular' dynamic variables *last_visitweeks* and *last_spending*, they capture deviations from business-as-usual carry-over effects due to the Savings Week event. Correlation between the variables used in the store visit model can be found in Table 4.4, whereas Table 4.5 displays the correlation for the variables used in the spending mode.

4.6. Estimation Results

We first focus on the store visit equation, after which we will discuss the expenditure model.

4.6.1. Store Visit Incidence

Table 4.6 reports parameter estimates for the visit-incidence model. For simplicity of exposition, we discuss the estimated population means below (standard deviations of the mixing distributions are also reported in Table 4.6). The control-variable coefficients are significant, with the expected sign. Price and distance negatively affect the propensity to visit a store, while prices at competing retailers, assortment and ad spending exert a positive impact. The coefficient of retailer share is positive – pointing to 'explained heterogeneity'– as is the *last_visitweeks* parameter – indicating that shoppers have a tendency to revisit a retailer they shopped at before. These results are in line with previous findings. The scale parameter for HDs is 1.14 (compared to a scale parameter for TDs fixed to 1). Whereas the correlation between the error terms of hard-discounters and traditional supermarkets is not significantly different from zero (suggesting that visiting a traditional chain in a certain week does not necessarily come at the expense of visiting a hard discounter), the error correlation for traditional supermarkets is -.24, and between hard-discounters -0.04, illustrating that traditional supermarkets seem to be closer substitutes than hard-discounters.

--- Insert Table 4.6 about here ---

Turning to the Savings Week effects, we find positive and significant dummy coefficients for all five events. Not all events affect retailer patronage equally: compared to the other events, “Euroweken” and “Hamsterweken” lead to much larger increases in store visits during promotion weeks. Competing events do not systematically lower the likelihood to visit competitor stores, if anything, the model results indicate that consumers may increase the likelihood to visit competing retailers. Possibly because in Saving Weeks they are more included to visit multiple stores simultaneously. Albeit the magnitude of this effect is very small and not economically significant, it implies that the systematic negative correlation between retailers appears to be less in weeks with events. The negative parameter associated with the retailer share-event interaction indicates that Savings Week events draw disproportionately more from non-loyal households – suggesting that the events, indeed, may haul in new customers for the retailer.

We find evidence that consumers postpone store visits in anticipation of the event: the lead effect is negative and significant. In addition, the coefficient of the lagged-event variable is negative, pointing to a negative effect of event weeks on regular revisit-tendency of households. Hence, we find both a pre- and post-promotion effect.

--- Insert Table 4.7 about here ---

4.6.2. Conditional Spending

Table 4.7 contains parameter estimates for the expenditure model. The store-dummy coefficients represent the average expenditure across households for each store. The control-variable coefficients indicate that households tend to spend more at their customary store (positive and significant coefficients for the retailer share and average spending variables), and when the retailer is located further away – making big trips more worthwhile. Also, households that spent a lot at the store in previous weeks, also spend more in the current week, possibly as a result of habitual buying. Price is positively related to spending within a retailer, which, given that the dependent variable is expressed in monetary value (i.e. unit price multiplied by the number of units purchased), may simply point to inelastic demand. We find an own-price elasticity of 0.35, comparable to basket effects found in previous studies (van Heerde et al. 2008), which points to inelastic demand; increases in quantity being more than compensated by drops in unit price. A negative cross-price was found, that may be consistent with a temporary income or windfall effect (Chandon et al. 2000) that was also observed in previous studies (van Heerde et al. 2008), consumers' lower expenses in one chain may lead them to spend more in another (visited) store. The advertising effect is positive, which may indicate that media spending attracts larger-basket shoppers, or directs their purchases towards higher-priced items. The size of the assortment does not significantly influence the amount spent at a retailer, once in store. Lastly, the coefficient of the correction factor is highly significant, underscoring the need to incorporate a selection-bias correction.

Three out of the five Savings Week events have a positive effect on spending within the focal store (positive coefficients for the event-dummies in Table 4.7, only "Hollandse Prijsweken" and "Euroweken" have insignificant spending coefficients).[37] Given that these events are often thought of as 'big saving' opportunities, it is not surprising that people buy larger quantities (by stocking up, and/or shifting purchases away from other stores) during these promotional events, and that this quantity increase more than compensates for the lower prices. Interestingly, unlike the effect on store visits, especially customary store shoppers spend more during the promotion event, as evidenced by the positive coefficient of the

[37] During the "Hollandse Prijsweken" there were deals on fruit and vegetables, one of the factors that may explain a differential effect for this event, as baskets may have been smaller rather than larger.

retailer share-event interaction. An alternative explanation is that non-loyal customers buy the majority of their purchases from their regular store and only buy a subset of products on deal during the savings weeks.

The impact of the competitor-event variable is negative, but small in comparison to all the other event effects (less than 3%). Moreover, in addition to the evidence found of consumers postponing their store visits, Table 4.7 points to a negative lead-effect on spending. So, although events are not advertised beforehand, their recurring nature may lead consumers to both visit and buy less at the store if they suspect an upcoming event. In contrast, we find evidence of increased spending in the week immediately following the event.

4.7. Implications

While the coefficients in Tables 4.6 and 4.7 shed light on the significance of different event-effects, they do not give a clear picture of the overall effect sizes, nor of the net implications of the (sometimes countervailing) dynamics. In this section, we therefore use some stylized simulations to provide such insights.

4.7.1. Average Effects During Event Weeks

First, to get a grip on the magnitude of the impact during event-weeks, we proceed as follows. For each household in the data set, we first determine its posterior parameters (based on the estimates in Tables 4.4 and 4.5, and using the approach described in Train 2009). We then calculate for each household, retailer and event-week; the average visit-propensity (weekly spending conditional on a visit) when the Savings Weeks event dummy for a specific event at the retailer is turned on and, for each Savings Weeks event; obtain the average store visits rates and spending across households and event-weeks. Next, we compare these figures to the households' average observed baseline propensity to visit the retailer (baseline spending at the retailer).[38] Specifically, we calculate the percentage change in weekly visit propensity (conditional store spending) for each Savings Weeks event. Table 4.8 summarizes the results.

--- Insert Table 4.8 about here ---

The left-side column shows that Savings Weeks events lead to substantial and economically relevant increases in store visit propensity. On average, the fraction of households with a visit during event weeks goes up by 9.61%. At the same time, the effect varies strongly across events. Two events stand out, “Euroweken” and “Hollandse Prijsweken”: with 13.0% and 13.3% increases relative to the baseline visit propensity - these events appear very successful at drawing households to the retailer.[39] Hamsterweken and Super Toeter weken have a slightly smaller draw, ranging from 8.6-9.8%, whereas I Love Gratis weken has the smallest lift in visits (3.4%).

The right-side column reveals that, given that a store is visited, households spend substantially more during event weeks for four out of five events. The two most successful events at increasing spending (Hamsterweken and Super Toeter weken, with spending increases of 8.77% and 8.01% compared to the baseline, respectively) and “I Love Gratis Weeks” (1.53%) have a positive effect on spending, whereas Euroweken and Hollandse Prijsweken do not have any significant effect on consumer spending. An interesting observation is that Plus decided to stop “Hollandse Prijsweken” in 2012 (beyond the span of our data), corroborating our not-so- favorable findings for this event.

While Table 4.8 gives an overall flavor of the magnitude of effects during event weeks, several refinements are in order. For one, the estimation results in Tables 4.6 and 4.7

[38] We also used an alternative approach, in which we first compared the ratio of the retailer visit propensity with and without the event by household, and then averaged over households. This results in much higher averages (% increases), but mainly because the baseline visit propensity for some households is very low (leading to a very skewed distribution of the % increases across households, with a number of very large figures).
[39] Baseline average probability of visit are 0.24 and 0.07.

point to significant differences in reaction between more or less customary shoppers of the store. This is important, especially because retailers differ in the composition of their store clientele. Moreover, Tables 4.6-4.7 indicate that the event-effects extend beyond the Savings Weeks, with dynamics that deviate from those in business-as-usual settings. Below, we further explore these refinements.

4.7.2. Shopper Loyalty Differences

Table 4.9 indicates the effect of an ongoing event on store visit propensity and weekly spending, for (i) shoppers that do not belong to the store's regular customer base ('Non-Customers', with retailer visit share below 5%), (ii) regular shoppers but for whom the retailer is not the primary chain ('Non-Primary Customers', with visit share above 5% yet below 50%), and (iii) shoppers that allocate the majority of their visits to the store ('Primary Customers', with visit share 50% or higher). The table confirms that, during the event, these customer types get drawn to the store at a different rate. For instance, for the event 'Euroweken' at retailer C1000, relative to the baseline, the average visit propensity increases by 37.3% for current 'Non-customers'; compared to only 24.63 % for Non-Primary Customers, and only 6.89% for the store's primary customers. In absolute terms, this retailer's weekly visit propensity goes up by 5.2% for Non-Customers, compared to 5.5 and 3.1% for Non-Primary and Primary Customers. Clearly, this propensity to haul in 'new' shoppers depends on the current composition of the store's customer base (see also Table 4.9): the fraction of households that are Non-Customers being much larger for Plus and Super de Boer (over 70%) compared to the leading retailers C1000 (about 60%) and especially Albert Heijn (35%). In all, this indicates that events do substantially enhance store-visit incidence, both for regular and non-regular customers.

--- Insert Table 4.9 about here ---

The relative increase in spending, also, differs by customer type. Non-Customers and Non-Primary Customers exhibit stronger percentage increases in spending during event weeks. For instance, relative to the baseline, for 'Hamsterweken at Albert Heijn average spending goes up by 13.76% for current 'Non-customers'; compared to 11.79% for Non-Primary Customers and 9.15% for the store's primary customers. However, less regular store-shoppers also tend to purchase a smaller basket. When it comes to absolute changes in spending, customary households still show a substantially larger change in spending during a promo event. To illustrate, for Hamsterweken, the absolute spending increase (in Euros) for Primary shoppers amounts to 4.3, compared to 4.0 for Non-Primary; and to 3.8 for Non-customers of the store. This points to an interesting difference among the different shopper segments: the event especially increases visit propensity for less-regular store visitors, yet more strongly enhances absolute spending among more regular store shoppers.

4.7.3. Dynamic Effects

The question remains to what extent these extra sales (from more visits and higher spending) during the event period are offset by negative pre-event and post-event effects. To this end, we again compare the customer groups' average visit propensity and spending in the baseline scenario (no event occurrence), to those in the week preceding and following the event, as predicted by the model (and using the households' posterior parameters, starting from the estimates in Tables 4.6 and 4.7). Like before, for each of the two outcome variables, we calculate the indices relative to the baseline (from which the % changes can be obtained by subtracting 1 and multiplying by 100). Moreover, we multiply the visit propensity and spending indices to get an indicator for the total effect relative to the baseline. First, we do so by event, and for each type of week (pre-, during- and post-event). Next, we repeat this analysis per customer group (Non-Customers, Non-Primary Customers and Primary

Customers, based on their share of visits at the retailer – see also Table 4.9). Figure 4.1 illustrates the outcomes for all five events.

--- Insert Figure 4.1 about here **---**

Figure 4.1 shows that the negative lead effects (caused by a significant decrease in spending in the pre-event weeks, see Table 4.6) are small in size compared to the sales increase (from higher visit propensity and spending) during the event weeks. Moreover, though visits and spending become lower again following the event period, spending remains up to 3% higher than the baseline for Hamsterweken. For most other events, the spending in the post-event week is either lower, or hardly affected. Overall, this suggests that any post-promotion dips due to stockpiling, are more than offset by the expenditures of newly-attracted visitors and/or the spending increase among regular visitors during the event period.

4.8. Discussion and Directions for Future Research

4.8.1. Discussion

In recent years, triggered by cut-throat competition from both traditional players and hard discounters, grocery retailers have begun to add new weaponry to their promotional toolkit: Savings Weeks events. These events differ from the retailers' weekly 'business-as-usual' promotions in several ways: typically, they last for several weeks, are organized around an overarching theme supported with retailer in-store and media advertising, emphasize savings opportunities (involving deep price cuts or quantity discounts) across the basket bought at the store, and recur on a somewhat regular basis. Through such events, and because of their different characteristics, retailers hope to broaden their store clientele, and increase spending by their current customers. This study analyses the impact of such events on both retailer visits and spending.

Unlike business-as-usual retailer promotions (for which previous research found no or only weak evidence that they lift the shopper base), we find that Savings Week events can substantially increase the fraction of shoppers drawn to the store, by up to 13% during event weeks. Moreover, in relative terms, this lift is even higher for households that rarely patronize the retailer absent the event – underscoring that Savings Week events can, indeed, expand the retailer's customer base. Conversely, we find very little economical effect of similar events at a competing chain. As such, although we do not obtain clear evidence for direct store switching: consumers do adjust their store visit patterns (and not just reshuffling purchases among already visited stores) around event weeks.

Moreover, for 3 out of 5 events, given that the store is visited, shoppers also spend substantially more (across events, up to 10% more for the average store shopper). Whereas non-customary shoppers exhibit a larger relative spending increase, the highest absolute spending lift is obtained among more regular store shoppers. So, in all, the retailer benefits from increased visits and spending during the weeks of the event.

Because of their recurring nature, Savings Week events may trigger negative anticipation effects. We do find evidence that consumers postpone the chain visits in the week prior to the event, and somewhat lower their spending in anticipation of the event – although the latter effect is rather minor. Despite the fact that events entice consumers to buy in bulk at the retailer and 'stock up' at home; our results do not show post-event dips in spending at the chain, although visits are slightly lower. This may be because consumers increase their usage of the items they hold in store, and/or because they 'load up' at the expense of competing supermarkets. Based on these findings, it appears that, on the whole, gains in traffic and spending at the time of the event are not offset by pre- and post-event dips, and ultimately benefit the retailer. This counters the argument raised by some practitioners that Savings Week events fail to generate the hoped-for net increase in customers and sales, although we do note that there are substantial differences in effectiveness between events.

4.8.2. Directions for Future Research

Despite this optimistic picture, several potential caveats remain. First, we find important differences between events. Some events are more successful than others, and not all events do well. Though we find positive implications for three out of five events, two events show a mixed pattern of effects: during these events, retailer visits increase but spending is hardly affected. Though, across events, the increases in visit propensity and spending induced by the event appear related to the retailers' market share (higher-share retailers setting up more successful events), this does not explain the whole picture: one of the retailers has two different Savings Week events that differ highly in effectiveness. This leads to the question: what event-characteristics make certain Savings Weeks more effective than others? We leave this as an important question for future study.

Second, while we looked at the weekly store visit and expenditure implications of promotional events, retailers may have additional motives to set up these events. For instance, they use them to improve the store's price image (Meijsen 2014) and differentiate them from other stores. However, such effects may only materialize in a longer time frame than the one considered here. Similarly, retailers may profit in the long run by fostering loyalty among newly acquired customers and/or catering to their current clientele – issues that we leave for future study.

Third, our study pertains to only one country. Although similar promotion events exist in other countries (e.g. Kroger's Cart Buster Savings Event), the effects need not be the same due differences in retailer landscape and familiarity with saving weeks. The use of these events is a relatively recent phenomenon, raising several questions about shoppers' familiarity with the concepts and how this influences the impact of Savings Week events over time. Recurring Savings Week events may become more popular (as consumers recognize the concept) or, alternatively, less popular (as the surprise element disappears, and wear-out sets in). Also, lead effects may become more pronounced as consumers learn about the timing of the events. Our study provides several insights for retailers in countries where these promotional events are not yet a popular tool, but a more reliable assessment of the dynamic effects calls for a longer history of observations, and we leave it as a topic for future analysis. Similarly, some promotion events observed in practice bear similarity to our "Savings weeks", but differ in the type of product they apply to, and/or in the duration of the event. Examples can be found at French retailer Carrefour, which holds a "Crazy Month of Perishables", or in the apparel industry (e.g. "Crazy days" at Inno, a Belgian department store, or "Three crazy days" at Bijenkorf, a leading Dutch warehouse). Though we expect our findings to largely pertain to such events as well, a more formal analysis would be useful.

Fourth, while we expect Savings Week events to disproportionately draw non-customary households to the retailer - tempted by the potential savings they can obtain on a subset of their products - these consumers may merely visit the store for this select subset of products that is on promotion, which raises concerns about profitability of these newly acquired consumers. A similar question arises concerning the subsidization of customary consumers; even if the event increases their propensity to visit and/or spending, it remains to be seen what part of their basket consists of products that are on promotion, and how this will affect the retailer's bottom line. Further data exploration shows that, indeed, Savings Week events do inspire consumers to buy a larger-than-usual portion of the basket under promotional conditions (28.6% versus 15.8% in regular weeks), indicating that the extra sales are in large part driven by discounted items. This is especially true for non-customary store shoppers. Given that event-related discounts are often unusually deep, and often include selling prices below cost (Bijlsma 2009), the impact on the retailer's bottom line deserves more attention. For lack of data on pass-through and margins, we have to leave such profit analysis as a topic for future study.

Lastly, though our focus was on shopper reactions to given promotion events (which we treated as exogenous), there are interesting issues on the supply side. For one, more (frequent) Savings Week actions by one retailer may also trigger competitive events, and the question is: does this simply deepen the promotion trap? The answer is not clear-cut. Some retailers, with deeper pockets and more extensive communication, may benefit more, and use these events to weaken their competitors. As longer data periods, including more events, become available, analysis of the supply side implications becomes a fruitful topic for study.

Table 4.1: Retailer Descriptives

Retailer	Format	Relative market share (entire dataset) %	Market share sample %	Average visit rate[a]	Average spending per week[b] €
Albert Heijn	*Hi-Lo*	34.3	0.333	0.39	43.07
C1000	*Hi-Lo*	17.5	0.183	0.25	38.67
Aldi	*Hard Discounter*	13.6	0.142	0.20	27.36
Lidl	*Hard Discounter*	11.3	0.104	0.20	26.30
Jumbo	*EDLP*	9.9	0.087	0.13	42.04
Plus	*Hi-Lo*	7.4	0.093	0.07	31.22
SdB	*Hi-Lo*	6.0	0.058	0.06	33.54

[a] Fraction of weeks with a household visit, averaged across households
[b] Weekly mean spending per household, conditional on store visit. Expressed in Euros and averaged across households

Table 4.2: Frequency and Description of Events

Retailer	Event	Mean duration in weeks	Total weeks	Frequency	SKUs on themed promotion[a]
C1000	*Euroweken*	2.57	18	7	1168 (526)
AH	*Hamsterweken*	3.17	19	6	1543 (653)
Plus	*Hollandse Prijsweken*	3.00	12	4	652 (335)
C1000	*I Love Gratis weken*	3.00	6	2	1203 (526)
SdB	*Super Toeter Weken*	3.33	20	6	695 (337)

[a] Number of SKUs in promotion during savings week and regular weeks (in brackets).

Table 4.3: Variable Description

	Variable Name	Variable Description	Visit	Spending
Controls	$dummy\_retailer_r$	Dummy equal to 1 for retailer *r*	✓	✓
	$price^h_{rw}$	Weighted price index for household at each retailer ($price^h_{rw} = \frac{1}{C}\sum_{c=1}^{C}\left(\frac{p_{cwr}}{\overline{p_{cw}}}\frac{q_{hc}}{\sum_{c=1}^{C} q_{hc}}\right)$ over *c* categories bought by household *h* in week *w*)	✓	✓
	$comp\_price^h_{rw}$	Sum of weighted price indexes ($price^h_{rw}$)(for all competitors	✓	✓
	$assort^h_{rw}$	Weighted assortment index for household at each retailer ($assort^h_{rw} = \frac{1}{C}\sum_{c=1}^{C}\left(\frac{a_{cwr}}{\overline{a_{cw}}}\frac{q_{hc}}{\sum_{c=1}^{C} q_{hc}}\right)$)	✓	✓
	ad_spend_{rw}	Weekly media advertising expenditures for a retailer (in Euros), log transformed	✓	✓
	$dist^h_r$	Distance in km between household address and the nearest outlet of the retailer (updated quarterly), log transformed	✓	✓
	$season\_visits_w$	Aggregate visit index across households	✓	
	$season\_spending_w$	Aggregate spending index across households		✓
	$last\_visitweeks^h_{rw}$	Number of weeks with a visit by a household *h*, at chain *r*, in the previous four-week period	✓	
	$ret\_share^h_r$	Share of household *h*'s visits to retailer *r* over the entire observation period (see also Zhang and Breugelmans 2012)	✓	✓
	$last\_spending^h_{r,w-x}$	Spending by household *h* at retailer *r*, lagged x periods; x:1→ 4		✓
	$avg\_spending^h_r$	Average weekly expenditure (in Euros) of household *h* at retailer *r* (conditional on a visit)		✓
Promo variables	$event\ \#1_{rw}$	Dummy equal to 1 during "Euroweken" at C1000	✓	✓
	$event\ \#2_{rw}$	Dummy equal to 1 during "Hamsterweken" at AH	✓	✓
	$event\ \#3_{rw}$	Dummy equal to 1 during "Hollandse Prijsweken" at Plus	✓	✓
	$event\ \#4_{rw}$	Dummy equal to 1 during "I Love Gratis Weken" at C1000	✓	✓
	$event\ \#5_{rw}$	Dummy equal to 1 during "Super Toeter Weken" at SdB	✓	✓
	$comp\_event_{rw}$	Dummy equal to 1 if there is an event at any of the competing retailers in week *w*	✓	✓
	$ret\_share^h_r * event_{rw}$	Interaction between household retailer share and occurrence of an event at *r* in week *w*	✓	✓
	$lead\_event_{rw}$	Lead dummy indicating an event in the following week	✓	✓
	$lag\_event\_visit^h_{rw}$	Dummy activated only in the post-event week (0 otherwise), and equal to 1 only if household *h* visited *r* during the preceding promotional event	✓	
	$lag\_event\_spend^h_{rw}$	Equal to, in the post-event week, the maximum weekly expenditure of household *h* at *r* during the preceding event, and 0 in all other weeks.		✓

Table 4.4: Correlation Table Visit Equation Variables[a]

	$event\ \#1_{rw}$ (Euroweken)	$event\ \#2_{rw}$ (Hamsterweken)	$event\ \#3_{rw}$ (Hollandse Prijsweken)	$event\ \#4_{rw}$ (I Love Gratis weken	$event\ \#5_{rw}$ (Super Toeter weken)	$price^h_{rw}$	$assort^h_{rw}$	$lag\_event\_visit^h_{rw}$	$ret\_share^h_r$	$lead\_event^h_{rw}$	ad_spend_{rw}	$dist^h_r$	$comp\_event_{rw}$	$season\_visits_w$	$ret\_share^h_r * event_{rw}$	$last\_visitweeks^h_{rw}$
$event\ \#1_{rw}$ (Euroweken)																
$event\ \#2_{rw}$ (Hamsterweken)	-.015**															
$event\ \#3_{rw}$ (Hollandse Prijsweken)	-.015**	-.019**														
$event\ \#4_{rw}$ (I Love Gratis weken	-.007**	-.009**	-.009**													
$event\ \#5_{rw}$ (Super Toeter weken)	-.016**	-.020**	-.019**	-.009**												
$price^h_{rw}$	-.010**	.115**	.077**	.003	.054**											
$assort^h_{rw}$	.083**	.241**	-.031**	.050**	-.065**	.698**										
$lag\_event\_visit^h_{rw}$	-.009**	-.012**	-.012**	-.006*	-.013**	.058**	.090**									
$ret\_share^h_r$	.026**	.104**	-.053**	.016**	-.039**	.063**	.260**	.097**								
$lead\_event^h_{rw}$	-.017**	-.022**	-.021**	-.010**	-.022**	.080**	.070**	-.014**	.013**							
ad_spend_{rw}	.036**	.043**	.021**	.017**	-.005*	.001	.033**	.029**	.059**	.038**						
$dist^h_r$	-.018**	-.093**	.039**	-.013**	.066**	.058**	-.158**	-.069**	-.421**	.000	-.089**					
$comp\_event_{rw}$	-.067**	-.087**	-.084**	-.041**	-.088**	-.072**	-.073**	.009**	-.013**	-.055**	.035**	.004				
$season\_visits_w$	.040**	.021**	-.010**	-.003	-.028**	.005*	.001	.017**	.000	.026**	.319**	.009**	.041**			
$ret\_share^h_r * event_{rw}$	.241**	.517**	.054**	.147**	.106**	.077**	.155**	-.012**	.271**	-.022**	.035**	-.127**	-.086**	.016**		
$last\_visitweeks^h_{rw}$	.024**	.080**	-.046**	.012**	-.051**	.051**	.223**	.138**	.665**	.006*	.054**	-.420**	-.007**	.012**	.169**	
$comp\_price^h_{rw}$	.003	-.036**	-.022**	.000	-.017**	.280**	-.022**	-.006**	-.019**	-.023**	.014**	-.033**	.025**	.010**	-.013**	.052**

[a]: ** $p < 0.01$, * $p < 0.05$

Table 4.5: Correlation Table Spending Equation Variables[a]

	$event\ \#1_{rw}$ (Euroweken)	$event\ \#2_{rw}$ (Hamsterweken)	$event\ \#3_{rw}$ (Hollandse Prijsweken)	$event\ \#4_{rw}$ (I Love Gratis weken	$event\ \#5_{rw}$ (Super Toeter weken)	$price^h_{rw}$	$assort^h_{rw}$	$ret\_share^h_r$	$lead\_event^h_{rw}$	$avg\_spending^h_r$	ad_spend_{rw}	$dist^h_r$	$last\_spending^h_{r,w-1}$	$last\_spending^h_{r,w-2}$	$last\_spending^h_{r,w-3}$	$last\_spending^h_{r,w-4}$	$comp\_event_{rw}$	$season\_spending_w$	$ret\_share^h_r * event_{rw}$	$lag\_event\_spend^h_{rw}$
$event\ \#1_{rw}$ (Euroweken)																				
$event\ \#2_{rw}$ (Hamsterweken)	-.030**																			
$event\ \#3_{rw}$ (Hollandse Prijsweken)	-.012*	-.019**																		
$event\ \#4_{rw}$ (I Love Gratis weken	-.011*	-.017**	-.007																	
$event\ \#5_{rw}$ (Super Toeter weken)	-.012*	-.019**	-.008	-.007																
$price^h_{rw}$	-.009	.164**	.044**	.007	.033**															
$assort^h_{rw}$	.055**	.253**	-.047**	.031**	-.056**	.847**														
$ret\_share^h_r$	-.003	.063**	-.040**	.011*	-.009	.204**	.304**													
$lead\_event^h_{rw}$	-.022**	-.034**	-.014**	-.012*	-.014**	.080**	.094**	.033**												
$avg\_spending^h_r$	.014**	-.011*	-.006	.014**	.000	.087**	.049**	.015**	.009											
ad_spend_{rw}	.037**	.048**	.002	.012*	-.021**	.047**	.102**	.048**	.035**	-.025**										
$dist^h_r$	.007	-.060**	-.018**	-.007	.010	-.168**	-.217**	-.283**	-.022**	.009	-.034**									
$last\_spending^h_{r,w-1}$	-.012*	.042**	-.027**	-.001	-.003	.189**	.217**	.381**	.004	.366**	.004	-.102**								
$last\_spending_{r,w-2}$	-.018**	.025**	-.026**	-.006	-.016**	.176**	.206**	.379**	.000	.367**	-.015**	-.092**	.581**							
$last\_spending^h_{r,w-3}$	-.016**	.002	-.025**	-.011*	-.015**	.177**	.203**	.375**	.001	.368**	-.018**	-.094**	.577**	.577**						
$last\_spending^h_{r,w-4}$	-.014**	.013*	-.024**	-.005	-.022**	.173**	.204**	.380**	-.004	.366**	-.007	-.091**	.572**	.581**	.576**					
$comp\_event_{rw}$	-.084**	-.131**	-.054**	-.048**	-.054**	-.079**	-.102**	-.033**	-.047**	-.002	.007	.030**	-.019**	-.016**	-.007	-.018**				
$season\_spending_w$	-.042**	.059**	-.041**	-.038**	.059**	.000	-.012*	.002	-.042**	.000	.062**	.005	.177**	.170**	.157**	.128**	-.047**			
$ret\_share^h_r * event_{rw}$	.335**	.651**	.142**	.215**	.204**	.125**	.183**	.204**	-.039**	.017**	.044**	-.092**	.085**	.066**	.049**	.058**	-.151**	.023**		
$lag\_event\_spend^h_{rw}$	-.015**	-.024**	-.010	-.009	-.010	.082**	.089**	.077**	-.018**	.053**	.028**	-.031**	.115**	.125**	.134**	.051**	.040**	.041**	-.028**	
$comp\_price^h_{rw}$	.026**	-.068**	-.023**	.012*	-.006	.155**	-.112**	-.106**	-.021**	.132**	.001	.109**	-.004	-.003	-.002	-.006	.036**	.003	-.037**	-.016**

[a]: ** $p < 0.01$, * $p < 0.05$

Table 4.6 – Parameter Estimates Store Visit Model[a]

	Variable Name	Population Mean Coefficient	Population SD Coefficient
Controls	*dummy_C1000*	0.109*	0.150*
	dummy_Albert Heijn	-0.194*	0.982*
	dummy_Plus	-0.495*	1.095*
	dummy_Aldi	0.327*	1.250*
	dummy_Jumbo	0.207*	1.543*
	dummy_Lidl	0.473*	1.032*
	$price_{rw}^{h}$	-0.521*	0.150*
	$comp\_price_{rw}^{h}$	0.667*	0.091*
	$assort_{rw}^{h}$	7.485*	0.115*
	ad_spend_{rw}	0.056*	0.011*
	$dist_{r}^{h}$	-0.745*	0.397*
	$season\_visits_{w}$	0.525*	0.186*
	$last\_visitweeks_{rw}^{h}$	0.535*	0.179*
	$ret\_share_{r}^{h}$	4.090*	1.595*
Promo Variables	*event #1*$_{rw}$ *(Euroweken)*	0.620*	0.017*
	event #2$_{rw}$ *(Hamsterweken)*	0.616*	0.044*
	event #3$_{rw}$ *(Hollandse Prijsweken)*	0.397*	0.213*
	event #4$_{rw}$ *(I Love Gratis weken*	0.326*	0.040*
	event #5$_{rw}$ *(Super Toeter weken)*	0.356*	0.176*
	$comp\_event_{rw}$	0.004*	0.004*
	$ret\_share_{r}^{h} * event_{rw}$	-0.701*	0.210*
	$lead\_event_{rw}$	-0.145*	0.074*
	$lag\_event\_visit_{rw}^{h}$	-0.052*	0.003
Model parameters	*constant*	-7.836*	0.933*
	Scale parameter HDs (transformed)[b]	0.140* (1.150)	
	Correlation TS-TS (transformed)[c]	0.482* (-0.236)	
	Correlation TS-HD (transformed)	-0.002 (0.001)	
	Correlation HD-HD (transformed)	0.076* (-0.038)	

[a]: * = $p< 0.05$

[b]: log-transformed parameter was estimated

[c]: In order for the correlation parameter to be bound between -1,1, we estimated the following transformation $\left(\frac{2}{1+\exp(corr.parameter)}\right) - 1$

Table 4.7 – Parameter Estimates Expenditure Model[a]

	Variable name	Population Mean Coefficient	Population SD Coefficient
Controls	*dummy_C1000*	0.640*	-0.581*
	dummy_Albert Heijn	0.819*	1.016*
	dummy_Plus	0.184*	0.337*
	dummy_Aldi	0.676*	0.992*
	dummy_Jumbo	1.036*	-0.219*
	dummy_Lidl	0.630*	0.392*
	$price_{rw}^{h}$	0.995*	0.119*
	$comp\_price_{rw}^{h}$	-0.161*	0.035*
	$assort_{rw}^{h}$	-1.425	1.214*
	$dist_{r}^{h}$	0.112*	0.334*
	ad_spend_{rw}	0.005*	0.001*
	$season\_spending_{w}$	3.910*	1.426*
	$ret\_share_{r}^{h}$	2.708*	0.634*
	$last\_spending_{r,w-1}^{h}$	0.084*	0.100*
	$last\_spending_{r,w-2}$	0.093*	0.062*
	$last\_spending_{r,w-3}^{h}$	0.093*	0.016*
	$last\_spending_{r,w-4}^{h}$	0.038*	0.072*
	$avg\_spending_{r}^{h}$	0.004*	0.002*
Promo variables	*event #1*$_{rw}$ *(Euroweken)*	-0.014	0.124*
	event #2$_{rw}$ *(Hamsterweken)*	0.384*	0.068*
	event #3$_{rw}$ *(Hollandse Prijsweken)*	-0.021	0.166*
	event #4$_{rw}$ *(I Love Gratis weken*	0.063*	-0.097*
	event #5$_{rw}$ *(Super Toeter weken)*	0.306*	0.395*
	$comp\_event_{rw}$	-0.013*	0.044*
	$ret\_share_{r}^{h} * event_{rw}$	0.080*	0.005
	$lead\_event_{rw}$	-0.107*	0.072*
	$lag\_event\_spend_{rw}^{h}$	0.002*	0.020*
	correction_factor	0.481*	0.112*
	constant	-1.379*	-0.222*
	sigma[b]	2.242*	

[a] Dependent variable is scaled to allow for stability during estimation (DV=DV/10). *: p<0.05

[b] Due to interdependence and joint estimation of both models, this parameter needs to be estimated (maximum likelihood).

Table 4.8: % Increase in Store Visit and Spending by Event[a]

	Store Visits	Spending
event #1 (Euroweken)	13.00	-0.67
event #2 (Hamsterweken)	8.67	8.77
event #3 (Hollandse Prijsweken)	13.29	-1.23
event #4 (I Love Gratis weken	3.36	1.53
event #5 (Super Toeter weken)	9.76	8.01

[a] The percentage increase within the focal retailer is obtained by calculating, for each household (using posterior estimates), the counterfactual probability or spending (using augmented data in which we simulate the promo event taking place), averaging across households, dividing by the average baseline probability or spending across households, and subtracting one from this figure.

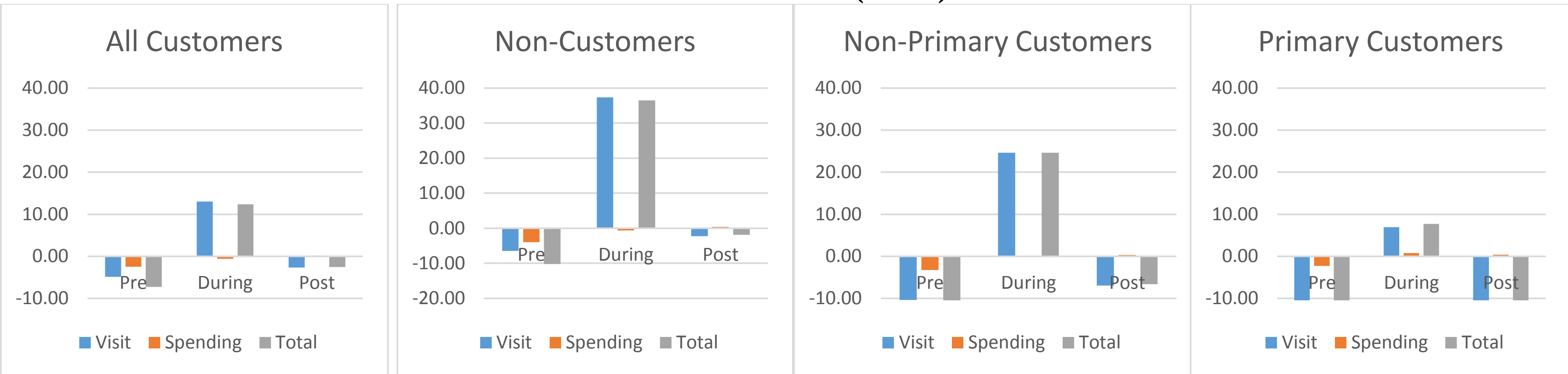
Table 4.9: Impact of Events by Household Type[a]

Retailer	Event	Non-customers (<=5%)			Non-Primary Customers			Primary Customers (>=50%)		
		% of households	*% increase visit probability*	*% increase spending*	*% of households*	*% increase visit probability*	*% increase spending*	*% of households*	*% increase visit probability*	*% increase spending*
C1000	*Euroweken*	59.7	37.31	-0.61	27.2	24.63	-0.02	12.4	6.89	0.76
Albert Heijn	*Hamsterweken*	34.9	32.24	13.76	36.6	19.10	11.79	27.2	3.97	9.15
Plus	*Hollandse Prijsweken*	78.5	31.75	-1.89	14.4	18.80	-0.89	7.1	1.37	0.31
C1000	*I Love Gratis Weken*	59.7	18.10	2.56	27.2	9.03	2.57	12.4	-1.90	2.58
Super de Boer	*Super Toeter Weken*	72.8	29.83	11.87	21.1	16.76	10.04	5.4	-1.36	7.73

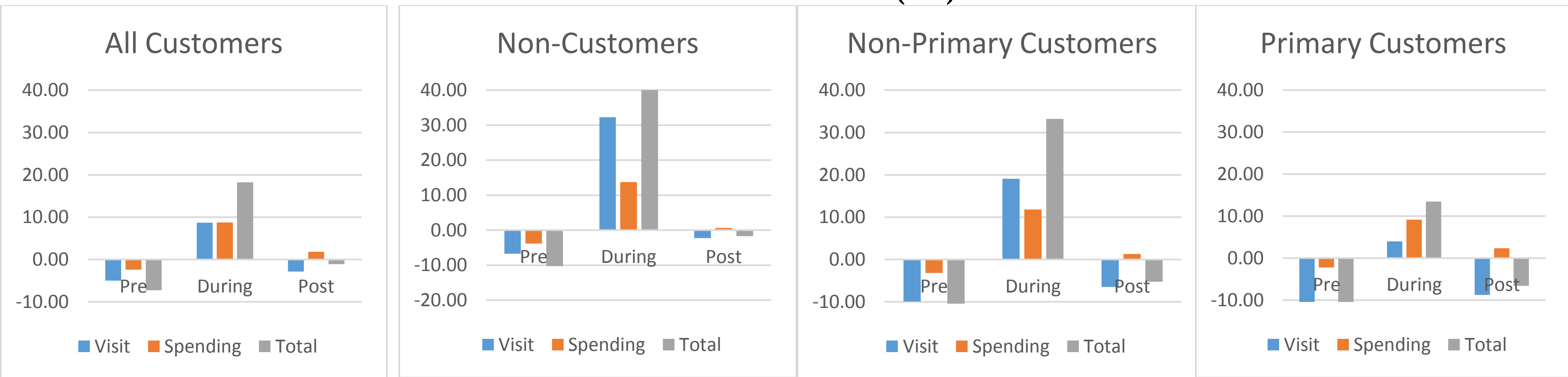
[a] Calculations were done in a similar fashion as discussed below Table 4.7. For each customer type, the % change in visit probability and spending was calculated for .1 grid values of retailer share, and then averaged across households grouped in that customer-type.

Figure 4.1: Dynamic Effects of "Saving Weeks"

Panel A: Euroweken (C1000)[a]

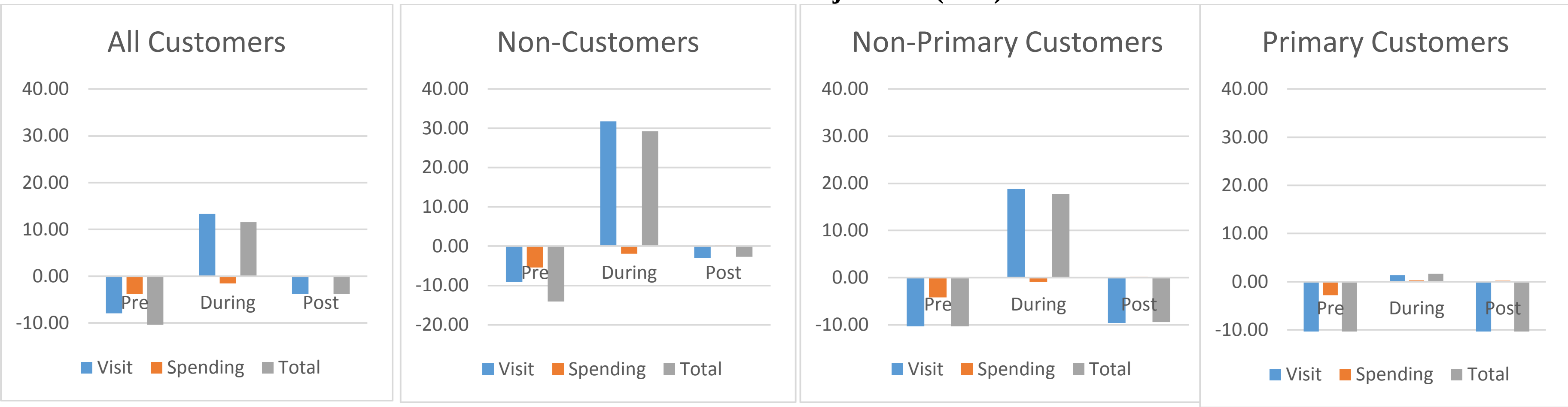


Panel B: Hamsterweken (AH)[a]

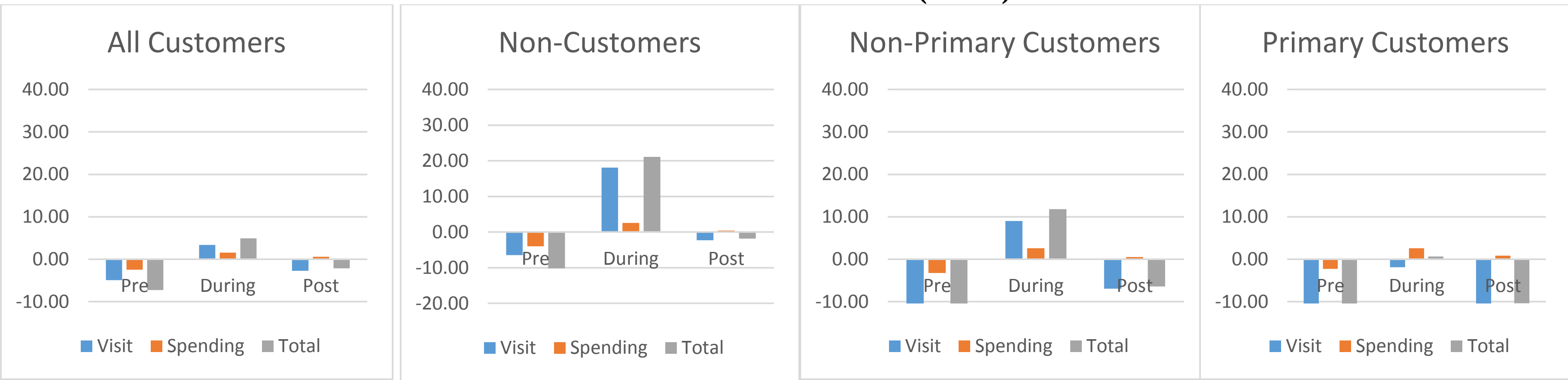


[a] Y-axis features the averaged combined effect (in Euros) of visit increases and spending for each group.

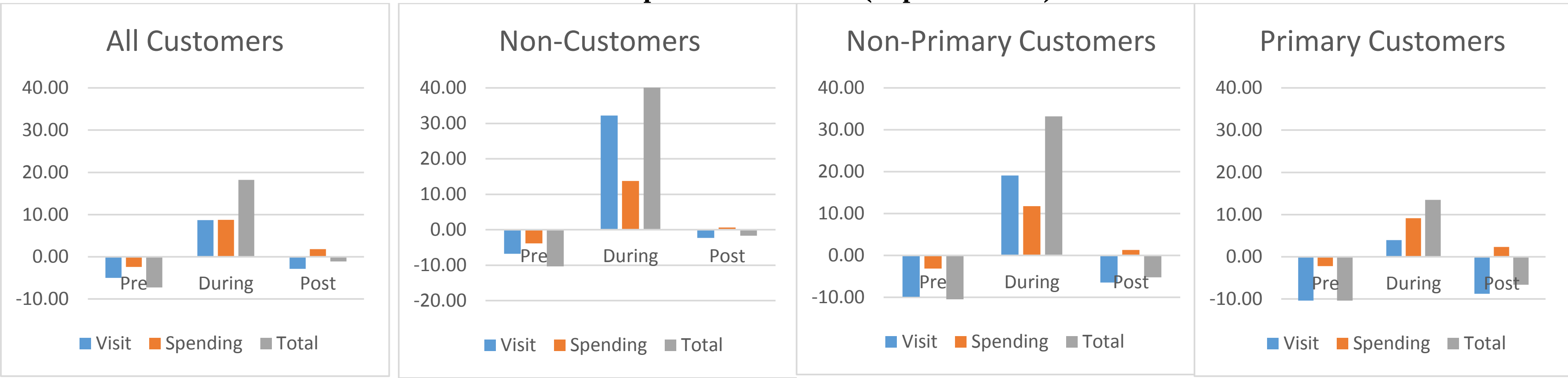
Panel C: Hollandse Prijsweken (Plus)[a]



Panel D: I Love Gratis Weken (C1000)[a]



Panel E: Super Toeter Weken (Super De Boer)[a]



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